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Hurricane Harvey: A quantitative approach to assessing the accuracy of National Water Model forecasted inundation

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Hurricane Harvey: A quantitative approach to assessing the accuracy of National Water Model forecasted inundation

by

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Dedication

To my parents

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Abstract

Hurricane Harvey: A quantitative approach to assessing the accuracy of National Water Model forecasted inundation

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The impact of Hurricane Harvey has stressed the need for accurate flood inundation forecasts to aid emergency response. The National Water Model uses predicted rainfall to produce forecasts of discharge and then generate flood inundation maps. To confidently employ flood forecast models for future events, we first need to assess the accuracy of these flood maps. The National Water Model combined maximum river discharge values for the affected Texas region and Height Above the Nearest Drainage (HAND) to calculate the extent of inundation from Hurricane Harvey. We compared this predicted inundation extent with a database of over 2000 high water marks gathered by the U.S. Geological Survey. At each high water mark location we calculated the difference of inundation depth between the National Water Model prediction and the measured high water mark. We find that the prediction has low bias with a mean difference of 26 cm, although there are far larger depth differences at individual locations. For approximately one-third of the comparisons made there is less than one meter of vertical difference between the National Water Model forecasted depths and the observed high water marks. We hypothesize that

channel features such as slope, length, and stream level are factors which influence the accuracy of the forecasted inundation depths, and present relationships found between these features and the accuracy of their forecasts. From this analysis, we find that the presence of pluvial flooding and storm surge is likely to obscure significant trends between these channel factors and prediction accuracy as the National Water Model models only fluvial flooding. We find that in regions where the model over-predicts inundated depth, slope and stream level are strong predictors of accuracy.

Table of Contents

List of Figures x

Chapter 1: Introduction 1

1.1. Overview/Motivation 1

1.2. Research Questions 4

1.3. Significance of Work 4

Chapter 2: Literature Review 5

Chapter 3: Data and Methods 8

3.1. Height Above the Nearest Drainage and Flood Inundation Mapping 8

3.1.1. General Framework 8

3.1.2 NWM Methodology for Forecasted Inundation Mapping 9

3.2. Comparison of NWM Inundation To USGS High Water Marks 10

3.3. Background on Harvey/Texas Study Region 13

Chapter 4: Results 20

4.1. Research Question 1: What terrain characteristics and/or channel features affect the level of disagreement between prediction and observed values? 20

4.2. Research Question 2: What is the connection between particular terrain characteristics and mapping inaccuracies, and what conclusions can be drawn from assessing the link? 31

4.3. Research Question 3: What steps and/or metrics are feasible for quantifying and minimizing the inconsistencies between predicted and observed values? 38

Chapter 5: Discussion 39

5.1. Research Question 1: What terrain characteristics and/or channel features affect the level of disagreement between prediction and observed values? 40

5.2. Research Question 2: What is the connection between particular terrain characteristics and mapping inaccuracies, and what conclusions can be drawn from assessing the link? 41

5.3. Research Question 3: What steps and/or metrics are feasible for quantifying and minimizing the inconsistencies between predicted and observed values? ...42

Chapter 6: Future Work and Conclusions 43

6.1. Future Work 43

6.2. Concluding Remarks 45

Appendix 46

Works Cited 53

List of Figures

Figure 1. General workflow of the National Water Model forecasted inundation mapping....10

Figure 2. Comparison of NWM forecasted inundation depth and USGS high water mark. 12

Figure 3. Study region: all of Southeast Texas and the Gulf Coast where Hurricane Harvey was predominant. The blue lines represent reaches from the National Water Model....15

Figure 4. Available high water marks (~2000) from the United States Geological Survey. 16

Figure 5. Harvey peak forecasted inundation extent generated from the National Water Model. 17

Figure 6. Forecasted inundation extent is overlaid with available Harvey high water marks. A close-up of the high water marks is shown in Figure 7....18

Figure 7. A close-up image of the high water marks. The image depicts the forecasted coverage along with predicted inundation depth. 19

Figure 8. Image *a* shows the correlation between absolute depth differences (error) and stream length. Image *b* shows the correlation between absolute depth differences (error) and channel slope. Error or absolute depth differences is defined as the deviation of National Water Model forecasted inundation depths from USGS high water marks. 21

Figure 9. Images *a* and *b* depict the relationship between absolute depth differences (error) and channel length for HUC-120200 and HUC-120401, respectively. 23

Figure 10. Images *a* and *b* show the relationship between absolute depth differences (error) and slope for HUC-120200 and HUC-120401, respectively............24

Figure 11. Image shows the correlation between absolute depth differences (error) and stream level for Southeast Texas and the Texas Coast. 26

Figure 12. Image *a* shows the correlation between absolute depth differences (error) and stream level for HUC-120200. Image *b* shows the correlation between absolute depth differences (error) and stream level for HUC-120401...27

Figure 13. Image depicts the spread of negative (under-prediction) and positive (over-prediction) error values of National Water Model predictions when compared to USGS observed high water marks. 29

Figure 14. Plot shows the distribution of the measure of National Water Model error.....30

Figure 15. Image *a* shows the correlation between absolute depth differences (error) and slope for all available points of comparison. Image *b* shows the correlation between absolute depth differences (error) and reach length for all points. 32

Figure 16. Image *a* shows the correlation between absolute depth differences (error) and stream level for all available points of comparison. Image *b* depicts stream levels “5” and “6” combined. 33

Figure 17. Image depicts normalized error as a function of stream level with stream levels “5” and “6” combined into stream level “5”. 34

Figure 18. Image *a* shows the correlation between absolute depth differences (error) and slope for NWM over-predicted points. Image *b* depicts error and reach length for over-predicted inundation points. 35

Figure 19. Images *a* and *b* shows the correlation between error by slope and reach length, respectively for NWM under-predicted points. 36
Figure 20. Image *a* shows the correlation between absolute depth differences (error) and stream level for NWM under-predicted points. Image *b* depicts error and stream level for over-predicted inundation points. 37
Figure A1. Hydrologic Unit Code (HUC) 6 basins within the study region. 46
Figure A2. Image *a* shows normalized absolute error as a function of length for all high water marks. Image *b* shows normalized absolute error as a function of stream level. Image *c* shows normalized absolute error as a function of slope. 47
Figure A3. Image *a* shows normalized absolute error as a function of stream level for over-predicted inundation by NWM. Image *b* shows normalized absolute error as a function of stream level for under-predicted inundation. 48
Figure A4. Image *a* shows error as a function of length for HUC6 – 120100. Image *b* shows error as a function of slope for 120100. 48
Figure A5. Image *a* shows error as a function of length for HUC6 – 120200. Image *b* shows error as a function of slope for 120200. 49
Figure A6. Image *a* shows error as a function of length for HUC6 – 120302. Image *b* shows error as a function of slope for 120302. 49
Figure A7. Image *a* shows error as a function of length for HUC6 – 120401. Image *b* shows error as a function of slope for 120401. 49
Figure A8. Image *a* shows error as a function of length for HUC6 – 120402. Image *b* shows error as a function of slope for 120402. 50
Figure A9. Image *a* shows error as a function of length for HUC6 – 120701. Image *b* shows error as a function of slope for 120701. 50

Figure A10. Image *a* shows error as a function of length for HUC6 – 120903. Image *b* shows error as a function of slope for 120903. 50
Figure A11. Image *a* shows error as a function of length for HUC6 – 120904. Image *b* shows error as a function of slope for 120904. 51
Figure A12. Image *a* shows error as a function of length for HUC6 – 121001. Image *b* shows error as a function of slope for 121001. 51
Figure A13. Image *a* shows error as a function of length for HUC6 – 121002. Image *b* shows error as a function of slope for 121002. 51
Figure A14. Image *a* shows error as a function of length for HUC6 – 121004. Image *b* shows error as a function of slope for 121004. 52

Chapter 1: Introduction

1.1. Overview/Motivation

Floods are one of the most deadly natural disasters in the United States. From flash floods and inland flooding to storm surges and coastal floods, the primary effects of floods include loss of life, damage to homes and businesses, and debilitated infrastructures. More recently, Hurricane Harvey and Hurricane Irma resulted in catastrophic flooding with the cost of damages estimated at $125 billion and $50 billion, respectively (Blake, E. S. and D. A. Zelinsky, 2018; Cangialosi *et al*., 2018.). Although different flood events vary in terms of magnitude, frequency, and distribution, the capability to predict and understand associated risks is imperative, especially when considering changes in the climate and rapid population growth and urbanization.

Historically, there has been a lack of detail and coordination in flood-governance structure between federal and local governments in the U.S. which is a contributing factor to the failure to mitigate flood-risks (Tullos, 2018). The wake of Hurricane Harvey and the aftermath as well as previous flood-related disasters have exposed the inadequacies of modern flood-risk governance policy and management. Therefore, major revisions are required in order to effectively and sustainably manage, mitigate, and understand flood risks (Tullos, 2018). Part of that process may involve the re-distribution of authority and resources for planning, mitigating, and recovering from floods among various entities, as well as breaching the gap between scientists and communities by educating and improving the public's understanding and awareness of flood risks (Tullos, 2018). Equally critical is the development of engineering practices that can swiftly assimilate real-time information to better inform and prepare the general populace for the natural disasters. Such practices entail flood modeling and inundation mapping which provide crucial information for land management and planning prior to and during flood-related events.

Flood mapping is an incredibly vital practice, containing an abundance of useful information, which is produced at a scale suitable for Emergency Responders. In addition to, flood inundation mapping across the conterminous U.S. would provide communities in all locations access to information to improve disaster resilience and emergency response efforts. Current, conventional flood-mapping practices rely on detailed measurements of channel cross sections in order to comprehensively characterize channel geometry and depict inundation extent with a degree of accuracy. Limitations to this approach, in addition to large expenses, include overlaps or gaps in channel coverage, as well as variations in performance between instruments (Zheng, 2015). Furthermore, practices reliant on the application of remotely-sensed imagery at a continental-wide scale lack the finer resolution needed to detect local streams that are critical during flood events (Zheng *et al*., 2018). A more recent and unconventional approach sees the combined application of high resolution topography and Height Above the Nearest Drainage (HAND) (Rodda, 2005; Renno *et al*., 2008; Nobre *et al*., 2011) for describing river geometry information and to generate flood inundation maps as a product (Zheng *et al*., 2018). HAND is a model that normalizes input national elevation datasets (NED) according to the local relative elevations/heights found along a drainage network (Nobre *et al*., 2011). In addition to, HAND depicts nearest drainage maps that are based on the vertical distance of each unit cell or pixel relative to the nearest stream cell it drains into (Nobre *et al*., 2011). For a complete description on HAND, see Nobre *et al*. (2011). The National Water Model (NWM) also uses the HAND method in conjunction with rating curves to produce inundation maps.

The National Water Center is a result of collaboration between the National Oceanic and Atmospheric Administration (NOAA) and other federal agencies. A hub for delivering a new generation of water information, the National Water center uses the National Water Model, informed by observational stream data, to simulate and forecast flood (river-based) inundation for the conterminous U.S. (Graziano, T. and E. Clark., 2017). For a technical description of the National Water model, see Gochis *et al*. (n.d.). The capacity to generate inundation maps from HAND has also recently been demonstrated at the national scale (Liu *et al*., 2016). The advent of HAND-based flood inundation maps from the National Water Model, to be used with any degree of confidence at the scale of emergency response and especially at a continental-wide scale, requires a robust accuracy assessment. This can be accomplished by evaluating their performance to various sources, such as United States Army Corps of Engineers (USACE) hydrodynamic models and United States Geological Survey (USGS) observational data, which have already been examined and standardized. By investigating the underlying factors that may influence flood mapping accuracy, we can further assist and protect communities, especially individuals in flood-prone regions, and enhance our knowledge of hurricane hydrology.

The main aim of this project is to initialize a framework for quantifying and assessing the inaccuracies that are associated with and plague the quality of forecasted inundation maps. The research will consider recent data from Hurricane Harvey as a case study. The work will investigate possible connections of mapping accuracy with underlying channel features/morphology and also suggest alternatives to attempt to rectify the differences between models/predictions and (true) observations.

1.2. RESEARCH QUESTIONS

1. What terrain characteristics and/or channel features affect the level of disagreement between prediction and observed values?

2. What is the connection between certain terrain characteristics and mapping inaccuracies, and what inferences can be drawn from assessing the link?

3. What steps and/or metrics are feasible for quantifying and minimizing the inconsistencies between predicted and observed values?

1.3. SIGNIFICANCE OF WORK

The value of this project is reflected in the findings concerning the connections of underlying terrain characteristics/channel features to the level of disagreement between models/predictions and observations. This research can help illuminate feasible measures to improve the accuracy and overall quality of flood inundation maps. There is also added value in being able to contribute to the study of hurricane hydrology. The step towards a methodical framework can serve as catalyst for further extensive exploration into other more naturally complex terrain characteristics; one evident parameter, Manning's roughness coefficient, has already been studied by Zheng *et al*. (2018), and investigations on Manning's n are ongoing at the National Water Center. From an operational standpoint, more accurate flood maps can enable the scientific community to deliver actionable intelligence for first responders, in addition to an overall improved capability to respond to extreme weather events.

Chapter 2: Literature Review

The advent of large-scale hydrologic and hydraulic modeling is in some ways due to the growth in hydrologic research and the collaboration of the science community, as well as advances in computational capacity and increased availability of terrain datasets, ranging from local to global extents and with greater quality in the resolution (Wing *et al*., 2017). In addition to, changes in the climate as well as population growth and rapid urbanization have placed increasing strains on the built environment and society as a whole to respond to extreme weather events and associated risks (Pregnolato *et al*., 2017). As such, there is a sense of urgency to combine current technology/modeling capacities and available data in order to enhance society's understanding of and ability to respond to such extreme weather events. This work is motivated in part by the same urgency and also the need to ably assimilate data and validate results in order to support decision makers and emergency responders.

Wing *et al*. (2017) explored and validated, against detailed local hydraulic models and flood hazard maps, the application of a 30-meter resolution two-dimensional hydrodynamic model of the contiguous U.S. to simulate fluvial and pluvial flooding in order to inform decision makers. Chen *et al.* (2017) explored the capacity for Lidar technology to serve as a hub for validating and improving flood inundation modeling. Similarly as important is in understanding the extents and impacts that are associated with floods. Dottori *et al.* (2016) presented a modelling framework for mapping flood hazards at a global scale by taking into account streamflow data derived from hydrological simulations of the Global Flood Awareness System (GloFAS). The methodology of Dottori *et al*. (2016) is then validated against reference data such as official hazard maps and satellite images. The combined efforts of their framework and GloFAS to successfully consider various compounding effects of flooding and accurately generate flood maps would mean a global scale flood database that is able to forecast and assess flooding impacts. Other researchers have taken up the role of addressing and validating uncertainties in models and measurements that are used to simulate and predict floods from real-time information (Ocio *et al*., 2017). The characterization of sources of uncertainty for a more objective definition of error can be incorporated in flood forecasting and enhance the quality of flood warning systems (Ocio *et al*., 2017). Among recent efforts, Pregnolato *et al*. (2017) focused less on model and instrumentation uncertainties and more on associated effects of flooding in the urban environment, specifically road networks. Pregnolato *et al*. (2017) developed a function/model to capture the interactions between floodwater and transport systems by quantifying associated perturbations in the road network system due to flooding (water levels). Recent work by Moftakhari *et al.* (2017) suggested a bivariate rather than a univariate approach for flood hazard assessment in order to account for compounding flooding effects from multiple drivers such as sea level rise and river flooding. Moftakhari *et al*. (2017) stressed that this approach is more true to nature since it more accurately represents coastal cities that are exposed to more than one driver, especially in a warming climate. The approach proposed by Moftakhari *et al*. (2017) is possibly informative in minimizing uncertainties and inaccuracies associated with flood inundation maps.

In considering the recent developments in flood research, it is just as informative to integrate more classic approaches with current technologies to tackle the challenges that are typical in a naturally complex environment. In this research, we employ the HAND model, previously applied to represent and classify soil water environments, in a more practical and local context (Nobre *et al*., 2011). The HAND model, in conjunction with a rating curve, is used to generate flood maps which are sources of useful information for flood hazard assessment. Applications of the HAND method in flood inundation mapping have been demonstrated by Rodda (2005) and Nobre *et al.* (2016). Recent efforts by Zheng *et al*. (2018) explored the use of the national elevation dataset (NED) and HAND to derive information on river geometry and estimate rating curves, which relate discharge to stage height. The work builds on initial efforts by Rodda (2005) and Renno *et al*. (2008) in using hydrological terrain analysis to derive river geometry attributes; the idea being that an improved understanding of the characteristics unique to the channel network can inform and enhance the accuracy of flood inundation maps. The evolution of hydrologic research sees major developments in terrain processing, such as the D8 and D∞ directional flow models that are based on the principle of steepest descent, and the exploration of higher resolution terrain data to augment flood mapping accuracy (O'Callaghan *et al.*, 1984; Tarboton, 1997). Rather than emphasizing higher quality terrain data and unique terrain processing tools, this research employs a more straightforward, statistical approach to address issues of accuracy in forecasted flood maps.

Chapter 3: Data and Methods

3.1. Height Above the Nearest Drainage and Flood Inundation Mapping

3.1.1. General Framework

Height Above the Nearest Drainage (HAND), representing the height difference between a cell and the nearest drainage cell in a raster grid, has been developed from remote sensed data and geospatial vector data such as flow lines and catchments (Liu *et al.*, 2016). The HAND values are computed from a hydrologic terrain analysis approach implemented in the TauDEM software (Tarboton, 1997; Tarboton *et al.*, 2008; 2009; Tarboton, 2016; Tesfa *et al.*, 2011). For each grid cell, a HAND value is identified which represents the height of water required to inundate that cell. A raster of HAND values is then maintained as a reference dataset for inundation mapping (Liu *et al.*, 2016). By suggesting a water level to the HAND raster, the extent of inundation is identified as all cells with a HAND value less than or equal to the input water level. Moreover, the depth of inundation can be obtained by taking the difference between the water level and the respective HAND value (Zheng *et al.*, 2018).

Flood inundation maps are generated by acquiring stream flow forecasts from the National Water Model and using a hydraulic property table to interpolate discharge to a uniform (assumed) water depth for a given stream (Liu *et al.*, 2016). The hydraulic property table is essentially a record detailing hydraulic properties of each reach of the National Hydrography Dataset Plus (NHDPlus) network that are derived from the HAND raster (McKay *et al*., 2012; Liu *et al.*, 2016). A defined set of stage heights with corresponding discharge values supplement each reach, in addition to other attributes such as surface area, bed area, and cross sectional area (Liu *et al.*, 2016). Thus, the general framework allows for a streamlined, automatic process to produce catchment-level inundation maps that are informed by the input DEM and river discharge. The ability to generate inundation maps based on terrain data has also been demonstrated at the national scale by the National Water Model (Liu *et al.*, 2016). For a complete description of continental scale inundation mapping, see companion papers Zheng *et al.* (2018) and Liu *et al*. (2016).

3.1.2 NWM Methodology for Forecasted Inundation Mapping

The National Water Center uses the National Water Model (NWM), informed by streamflow observational data from NOAA's Advanced Hydrologic Prediction Service (AHPS), the United States Geological Survey (USGS), and other sources including radar-gauge observation data, as part of their efforts to forecast inundation extents for the contiguous United States (Gochis *et al*., n.d.). AHPS in particular assists the National Water Center with prediction services by providing data on river flow from an hour to a season, including information such as bankfull depth, duration of flooding, and duration of drought (NWS, 2004). As part of their process to generate forecasted inundation maps, the National Water Model first forecasts streamflow/discharge (see Figure 1, image *a*) for a specified spatial and temporal scale (Maidment, D. and E. Clark, 2016). As seen in Figure 1, image *b*, the discharges are then converted to stage height using a hydraulic property table which is also represented by a rating curve (discharge-stage height relationship). See Zheng *et al*. (2018) for a complete description on rating curves and their development. By combining Height Above the Nearest Drainage (HAND) with values for stage height (Figure 1, image *c*), an inundation map is produced, depicting water coverage as well as the depth of inundation (seen in Figure 1, image *d*). Moreover, the inundation maps generated by the National Water Model are representative of flooding from channels (fluvial), which is an important point to consider when assessing their accuracy to observational data.

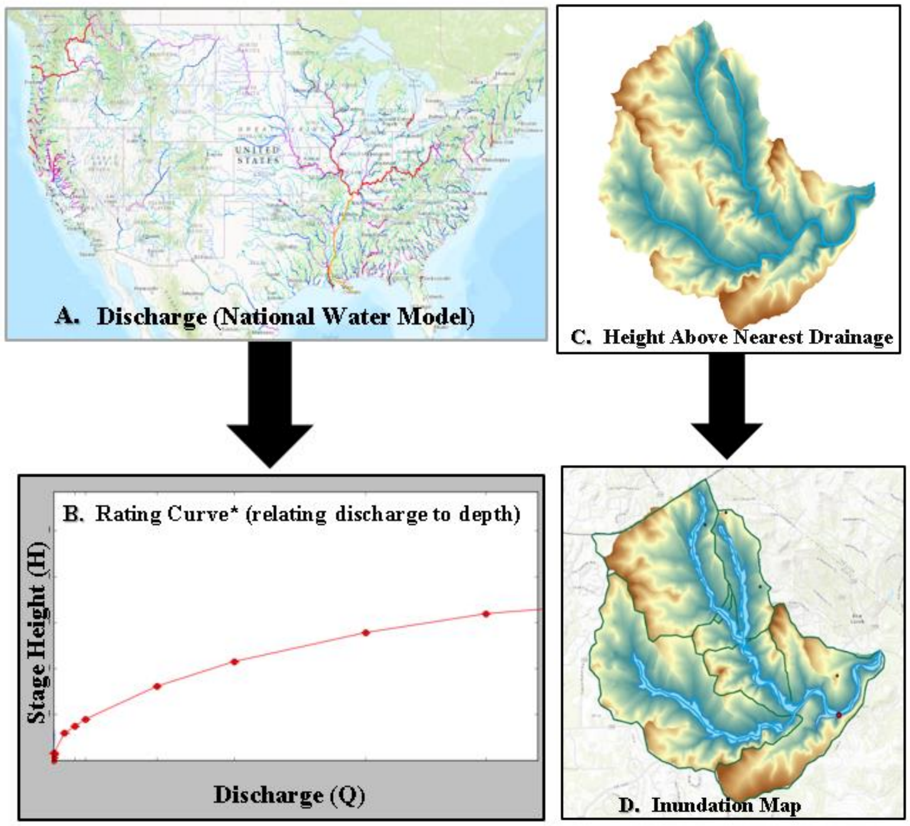

Figure 1. General workflow of the National Water Model forecasted inundation mapping.

3.2. Comparison of NWM Inundation To USGS High Water Marks

For a robust assessment of the National Water Model predictions, it is recommended to compare their performance to various sources such as remote sensed data, United States Geological Survey (USGS) high water marks, and United States Army Corps of Engineers (USACE) flood maps.

Approximately 2000 Harvey high water marks were provided by the USGS, spanning across our study region (seen in Figure 4). The NHDPlus reaches, seen in Figure 3, are provided by the National Water Model and serve as channel networks for our case study since they were within Harvey's zone of influence.

Our current effort evaluates the integrity of forecasted flood inundation maps from the National Water Model. We use Hurricane Harvey as our study case and compare National Water Model forecasted data to USGS observational data. Our method is thus split into two parts: 1) evaluate the accuracy of forecasted inundation extent and depth with measured high water marks from Hurricane Harvey and 2) investigate and quantify likely factors that affect the accuracy of the forecasted inundation.

Various statistical measures, such as absolute error and root mean square error, and each of which has specific biases, can be used to inform flood mapping accuracy. The primary metric used to assess accuracy in this study is defined as

$$Error = \widehat{yi} - yi \tag{1}$$

Where $\widehat{yi}$ represents the estimated or predicted stage height from the National Water Model and yi is the observed depth from USGS high water marks (see Figure 2). It is worth noting that the measured depth from a high water mark is relative to a geodetic datum which, in this framework, is in reference to the height above the ground.

Comparison to high water marks entails identifying the cells that include a high water mark and calculating its corresponding HAND value. If the reach that a particular cell flows into has a flood stage height greater than the HAND value then that cell is inundated. The difference between stage height and HAND represents either under-prediction (negative error) or over-prediction (positive error) of the National Water Model. Equation 1 is particularly useful for quantifying the deviation of predicted depths from (true) observed peak water levels. An additional metric used to describe the accuracy of forecasted inundation maps was error normalized by max forecasted inundation depth (converted from peak discharge) and is defined as

$$Normalized\ Error\ = \frac{\widehat{yi} - yi}{H_{max}} \tag{2}$$

Further investigations of error with reach length, slope, and stream level/classic stream order were conducted in an effort to quantify/characterize the relationship between error and specific channel features; chief methods include using descriptive statistics such as boxplots and scatterplots. This analysis was performed for all points of available high water marks.

It is worth mentioning that the overall accuracy of NWM forecasted inundation maps is weighted from the primary steps involved in map generation: 1) Rainfall to streamflow, 2) Streamflow to stage height, and 3) Stage height to inundation. In this project, the overall accuracy from converting rainfall to river discharge, discharge to stage height, and then stage height to inundation extent was evaluated. Further investigation into the accuracy of the rating curve, which describes the relationship between discharge and depth, has been made in Godbout *et al*. (in preparation).

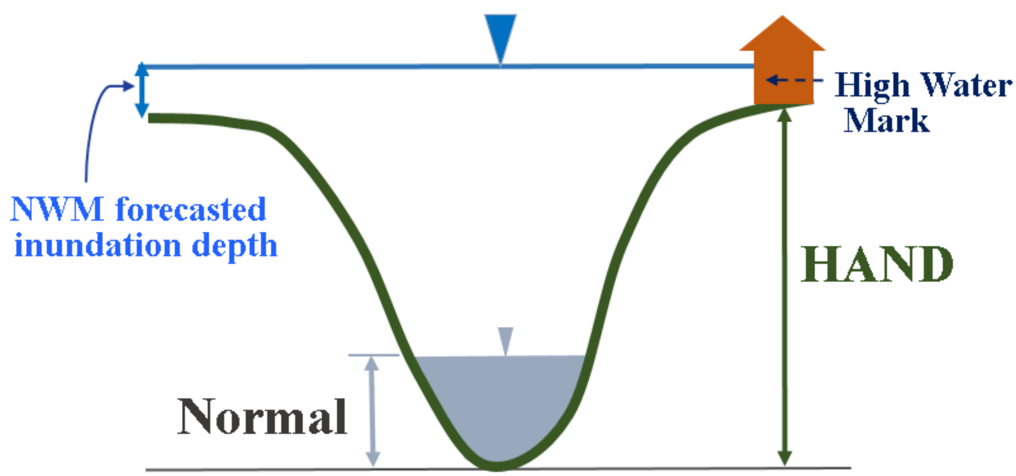

Figure 2. Comparison of NWM forecasted inundation depth and USGS high water mark.

3.3. Background on Harvey/Texas Study Region

Hurricane Harvey was a historic tropical cyclone in the U.S., both in scope and total precipitation. The five-day period brought more than 50 inches of rain in many regions of Texas, leading to catastrophic flooding. Harvey made landfall along the Texas coast near Port Aransas on August 25th as a category 4. It moved inland towards southeast Texas, bringing heavy rainfall and flash flooding and causing disastrous drainage issues, especially in cities like Houston (Blake, E. S. and D. A. Zelinsky, 2018). After moving offshore, Harvey made a third landfall in Louisiana, bringing more rainfall to the Norther Gulf States (Blake, E. S. and D. A. Zelinsky, 2018).

The study region consists of the Texas Gulf Coast and Southeast Texas. As previously mentioned, these are areas where Harvey was predominant. Furthermore, the reaches shown are downstream of AHPS sites, which also serve as sites of interest for the National Water Center to simulate and forecast flood inundation extents (NWS, 2004). Figure 5 illustrates NWM max forecasted inundation extent during Harvey, generated by requiring NWM reaches and peak forecasted discharges. Image *a* displays the water coverage as well as information on the depth of the predicted inundation. This information is instructive for our comparison of predicted spatial depth and extent with USGS measured high water marks. As seen in Figure 7 the forecasted inundation extent does not encompass several high water marks; regardless, it is important to identify the difference in depths from our forecasted inundation level to the level of the observed high water mark, independent of whether the predicted depth is above (over-prediction) or below (under-prediction) the high water mark.

Recent hurricane events have largely spurred the creation of a community repository of archived hurricane data. The data archive was established with NSF RAPID funding by the Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI) in Hydroshare for organizing and sharing available hydrologic data and models from recent hurricane events (Hydroshare Development Team, 2016; Tarboton *et al*., 2014). Information from the repository includes observation data and streamflow, as well as simulation and prediction, flood inundation models, and flood documentations from organizations like the NWM, USACE, FEMA, Harris County Flood Control District, and the Texas Division of Emergency Management. By organizing and assimilating available hurricane data into current systems, we can assist research communities to further develop forecasting models, improve flood mapping accuracy, and advance our understanding of hurricane hydrology (Tarboton *et al*., 2017).

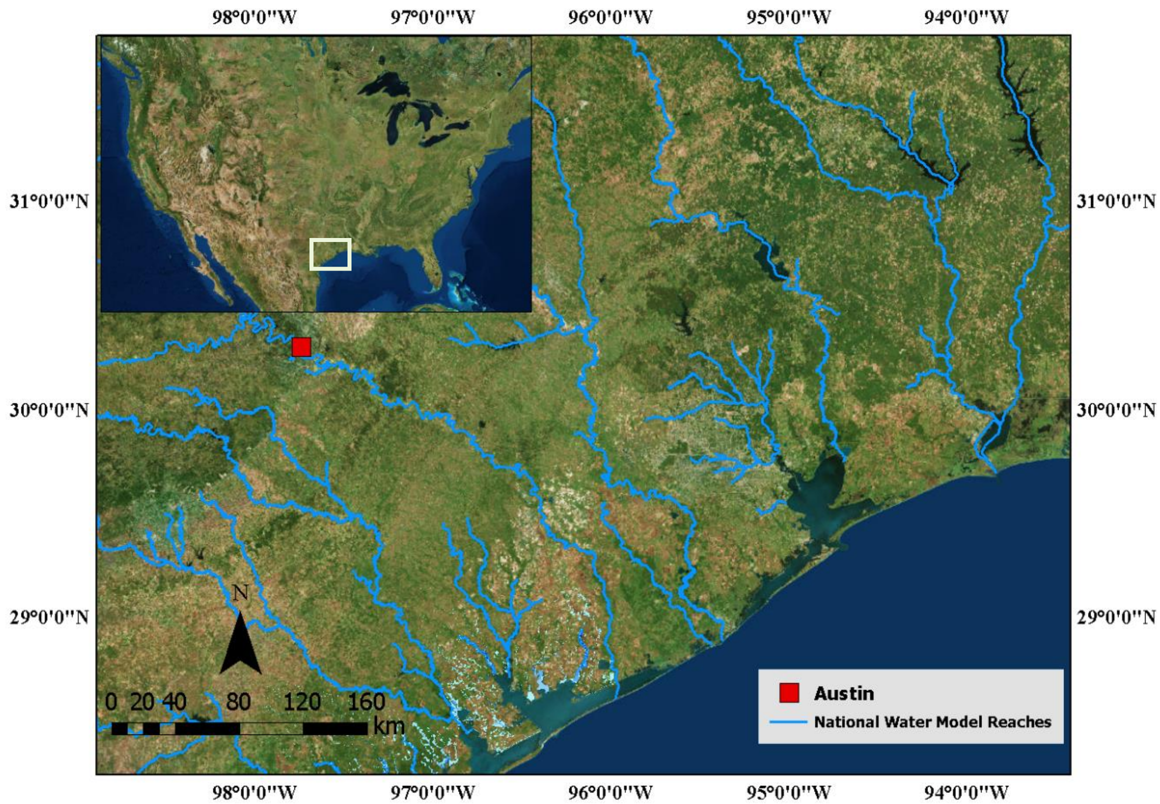

Figure 3. Study region: all of Southeast Texas and the Gulf Coast where Hurricane Harvey was predominant. The blue lines represent reaches from the National Water Model.

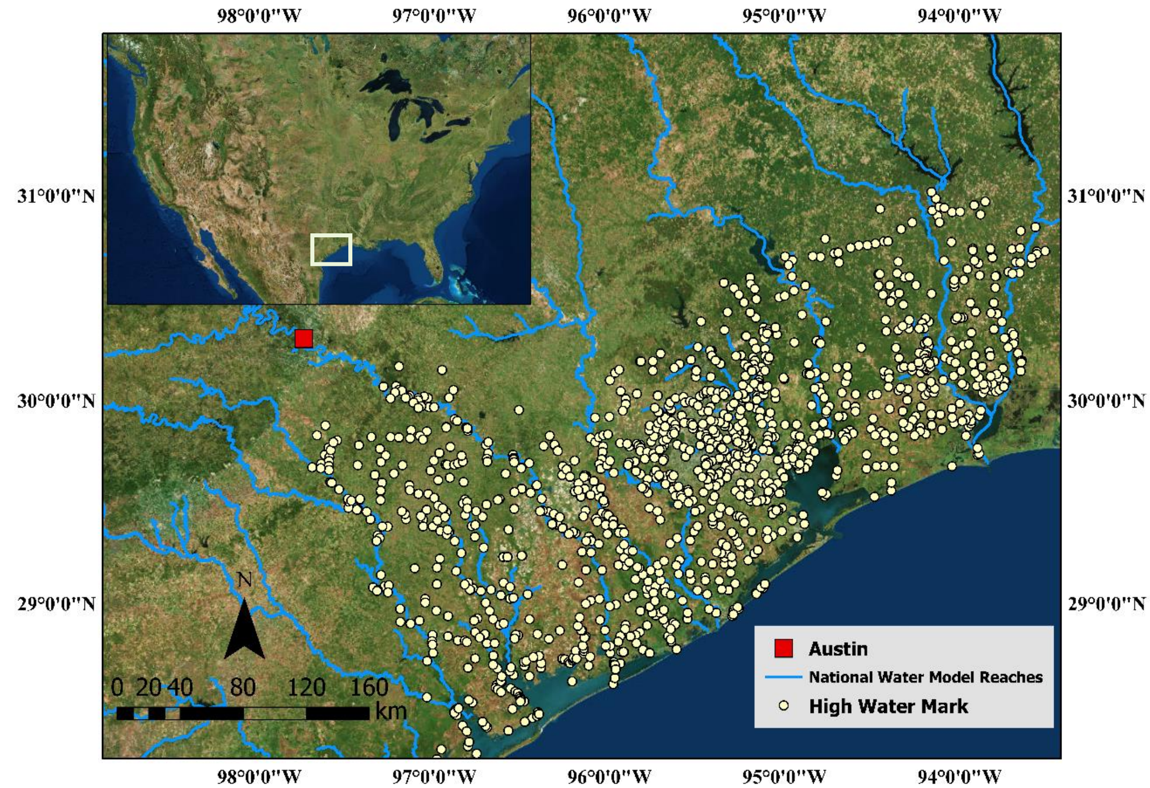

Figure 4. Available high water marks (~2000) from the United States Geological Survey.

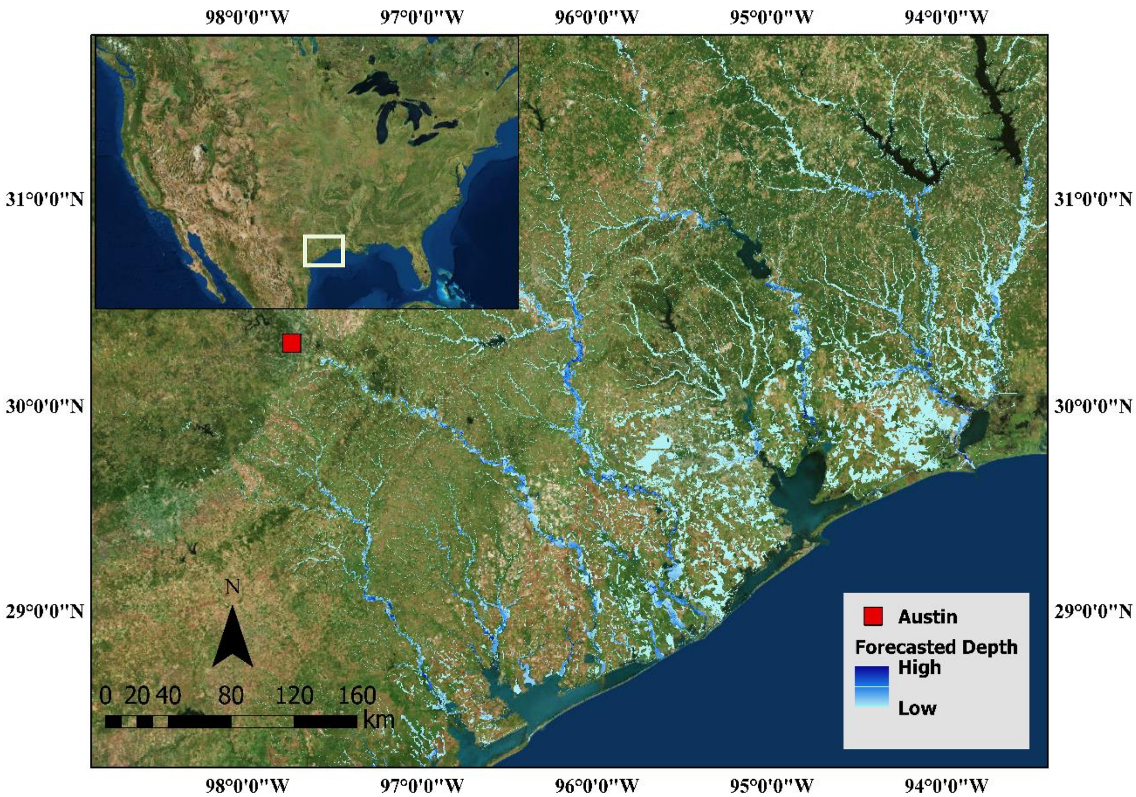

Figure 5. Harvey peak forecasted inundation extent generated from the National Water Model.

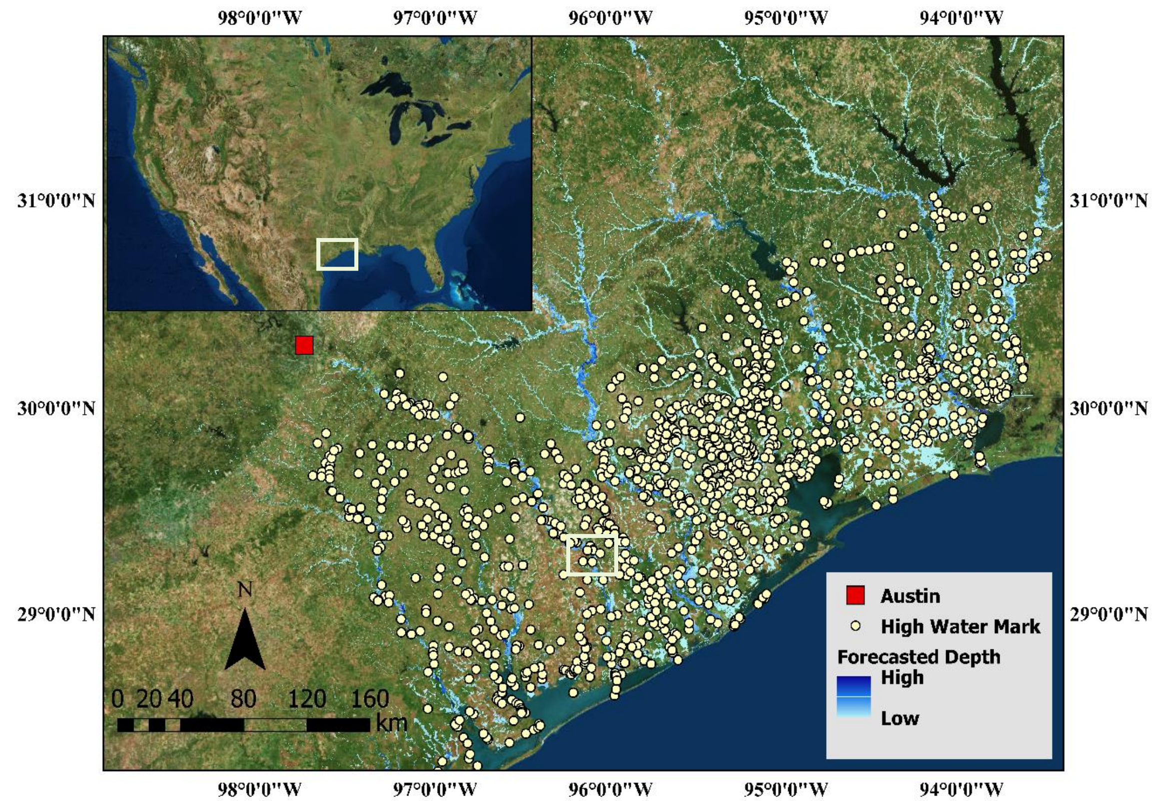

Figure 6. Forecasted inundation extent is overlaid with available Harvey high water marks. A close-up of the high water marks is shown in Figure 7.

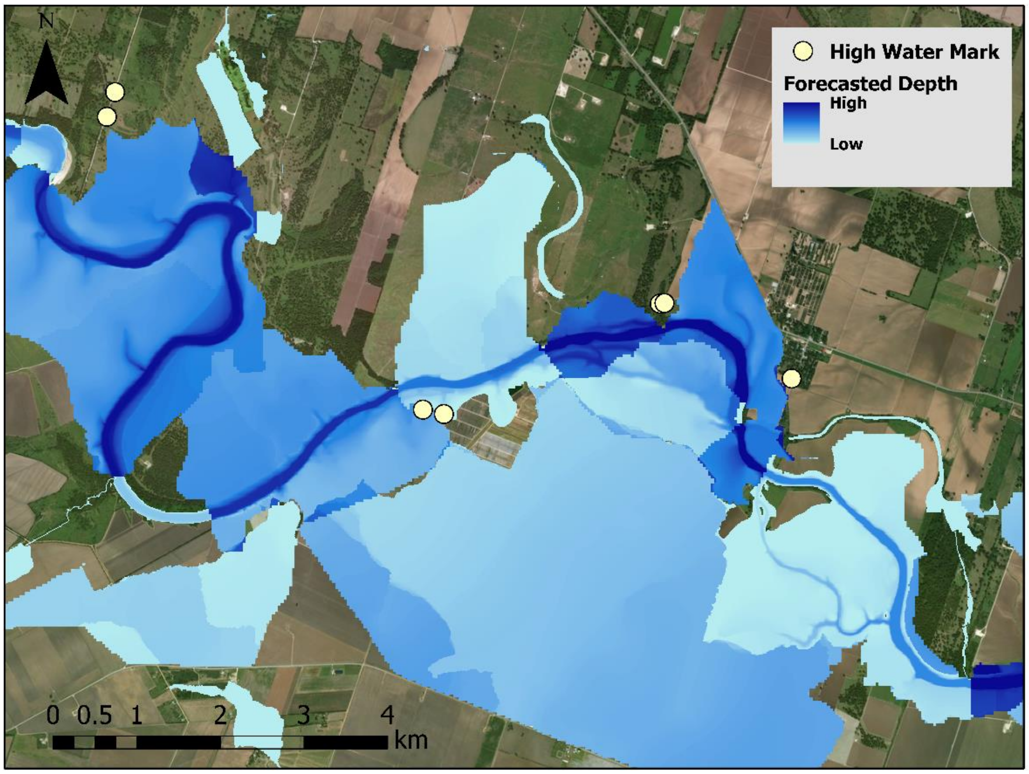

Figure 7. A close-up image of the high water marks. The image depicts the forecasted coverage along with predicted inundation depth.

Chapter 4: Results

4.1. Research Question 1: What terrain characteristics and/or channel features affect the level of disagreement between prediction and observed values?

It is worth noting that the nature and complexities associated with channel characteristics and morphology cannot be entirely captured by simplified modeling and statistical approaches. There are obvious limitations to using descriptive statistics to investigate the various channel features and their effect on modeling performance/predictions. As such, we consider only parameters that are relatively intuitive and straightforward to quantify. Parameters such as Manning's n are much more complex in nature and attempts to understand and predict its role in modeling accuracy is challenging. Though it is worth mentioning that there are other entities like the National Water Center that are leading the investigation on the significance of Manning's n.

Our initial studies included the use of scatterplots to assess the likely relationship between channel features like channel length and slope and the levels of disagreement between National Water Model predictions and USGS measured Harvey data.

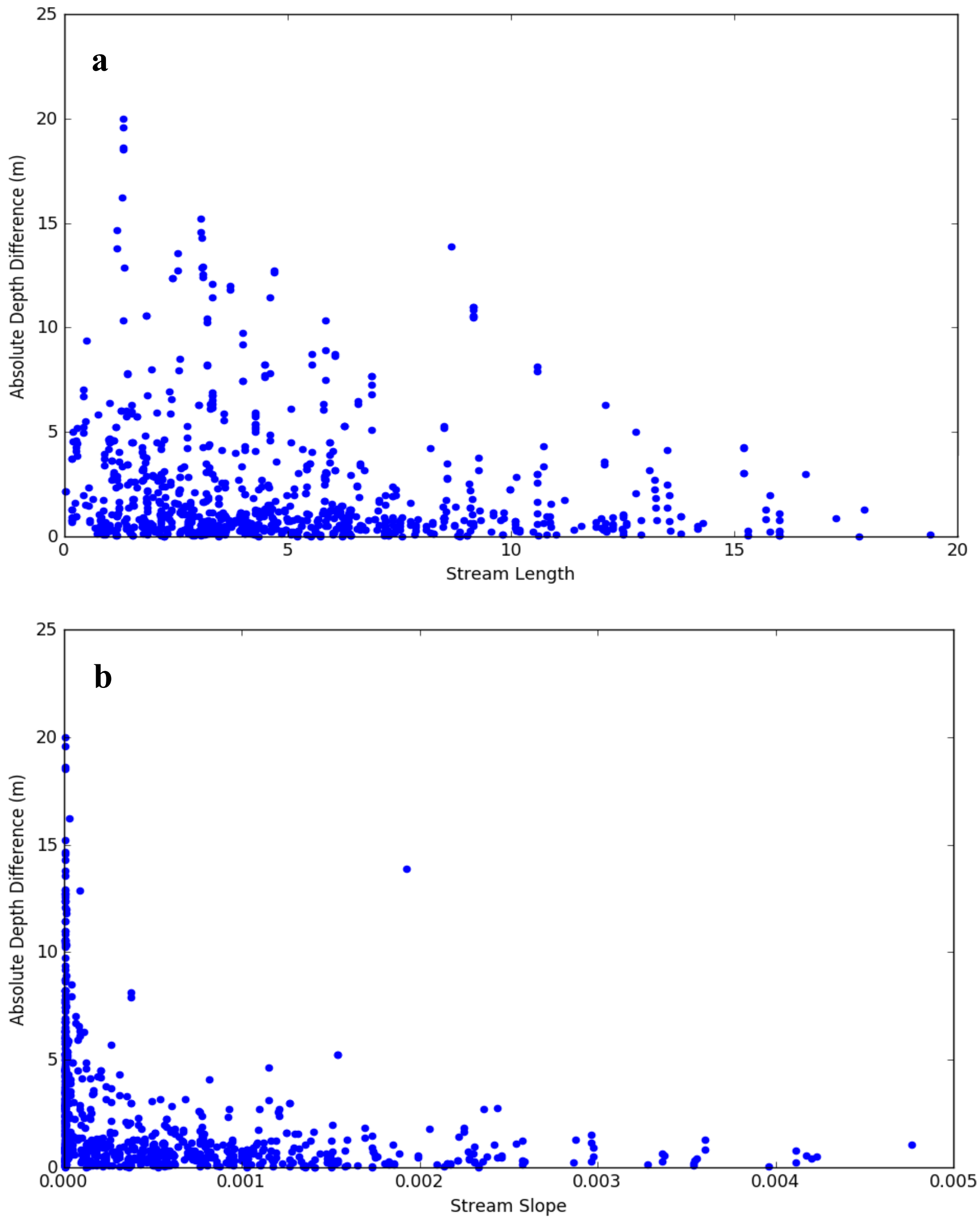

Figure 8. Image *a* shows the correlation between absolute depth differences (error) and stream length. Image *b* shows the correlation between absolute depth differences (error) and channel slope. Error or absolute depth differences is defined as the deviation of National Water Model forecasted inundation depths from USGS high water marks.

Because this analysis was performed across the majority of Southeast Texas and the Texas Coast, the subsequent question considered whether trends of error by length and slope exhibit differently when assessments are conducted more locally. In this case, we defined the term local as the extent of a HUC06 basin within the study region. As seen in the Appendix, Figure A1, there are about 11 HUC06 basins within the study extent. Analysis was performed for all HUC6 basins and two sample basins (120200 and 120401, respectively) are depicted by length and slope. HUC-120200 is approximately 25,736.71 square kilometers and HUC-120401 is estimated at 5980.28 square kilometers.

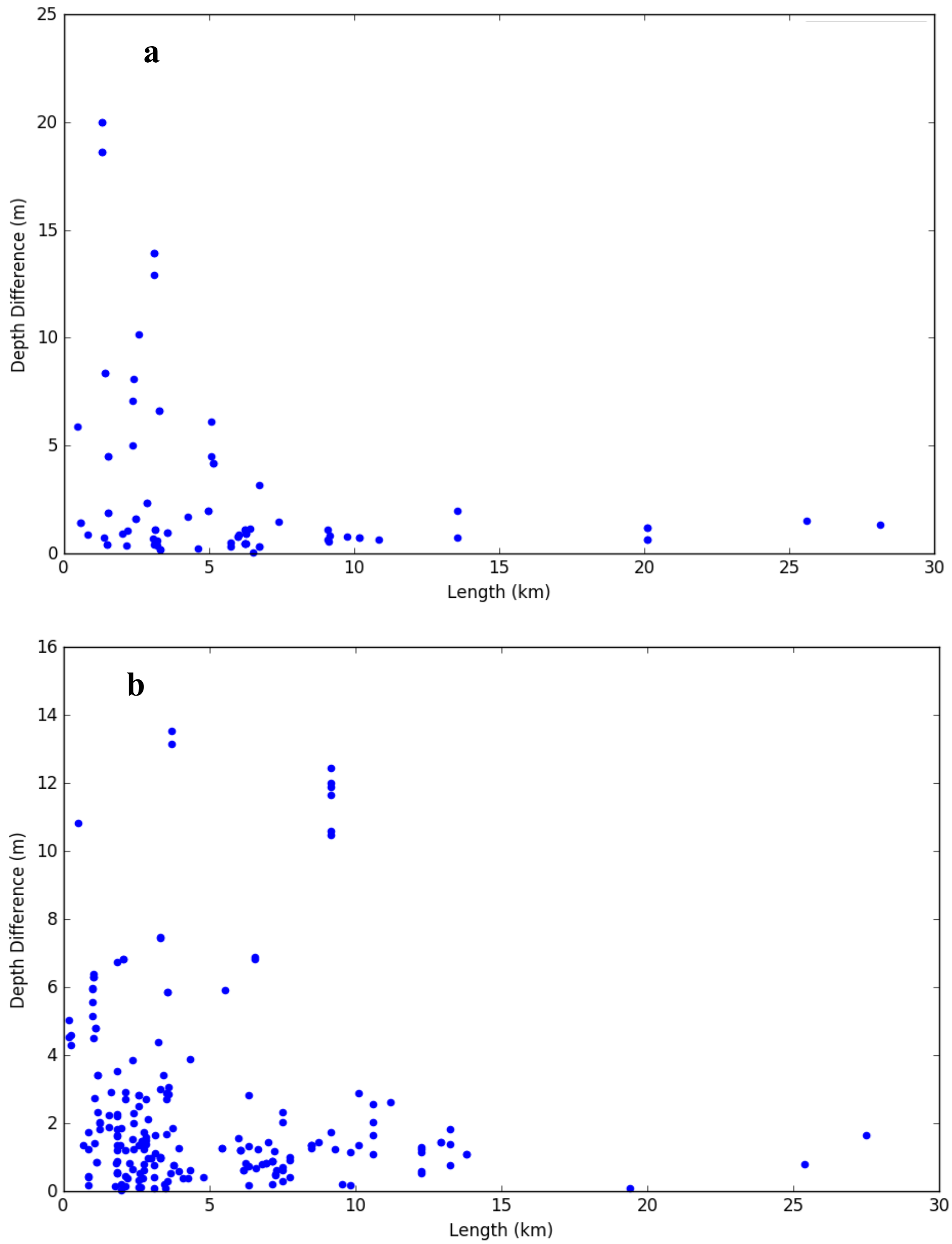

Figure 9. Images *a* and *b* depict the relationship between absolute depth differences (error) and channel length for HUC-120200 and HUC-120401, respectively.

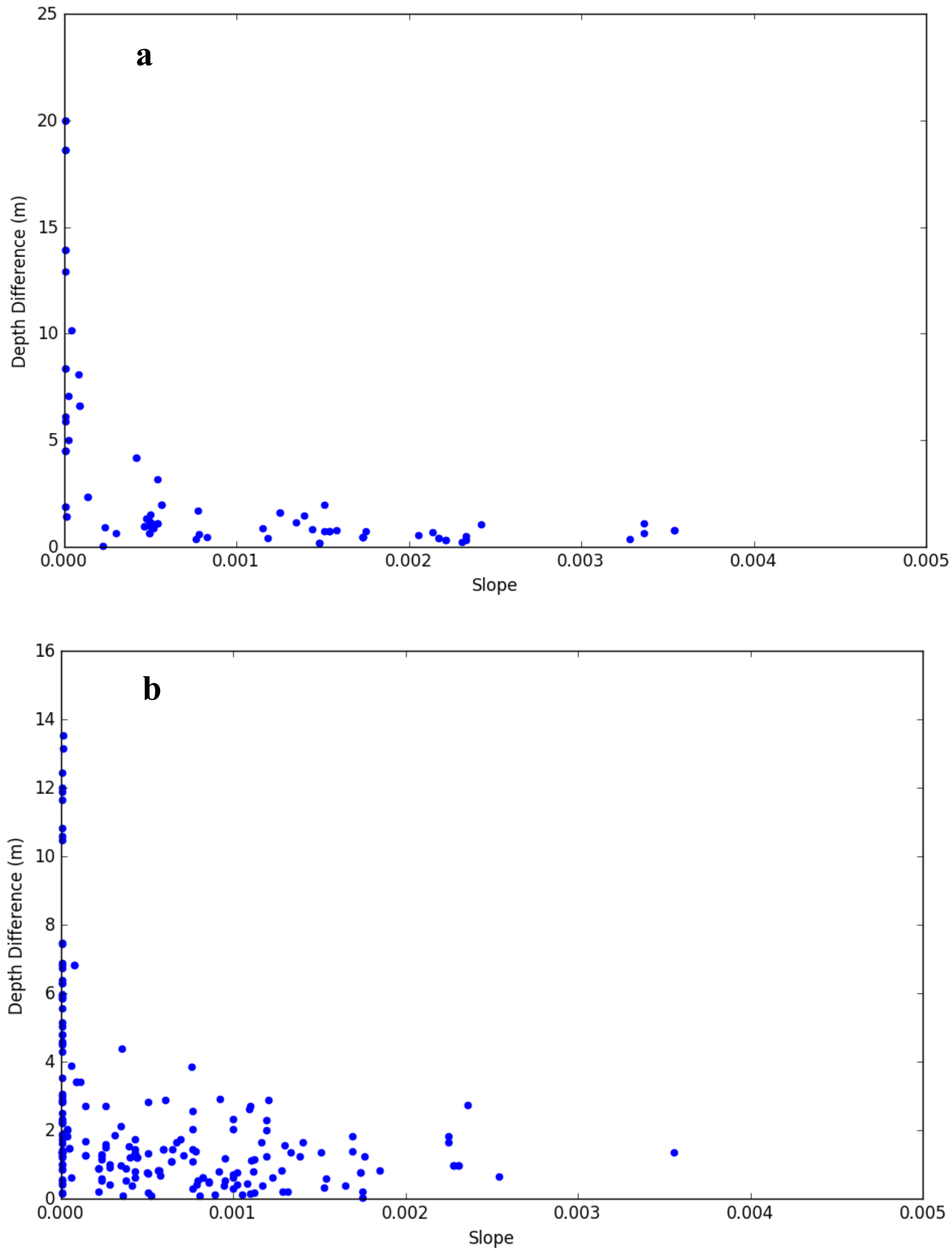

Figure 10. Images *a* and *b* show the relationship between absolute depth differences (error) and slope for HUC-120200 and HUC-120401, respectively.

Overall, results indicate a clear lack in any significant trends for our parameters of interest. In addition to, the number of data points (as seen in Figures 9 and 10) is somewhat lacking, thus making it difficult to accurately describe the trend. Figures 9 and 10, images *b* and *b*, respectively, contain many more data points than Figures 9 and 10, images *a* and *a*, respectively, though there is also a clear lack of trend.

Stream level (or classic stream order) is another effective parameter for describing the nature of channels. This numbering system (reciprocal of stream order) is defined as the hierarchy of streams from the mouth or outlet (which is allocated the number "1") upstream (Hack, 1957). The parameter is especially relevant when considered in the context of flooding. In addition to, we would expect tributaries to be particularly critical in the event of a flood. As such, we evaluated stream level and its subsequent effect on the level of disagreement/departure of predicted flood depths from observed high water marks.

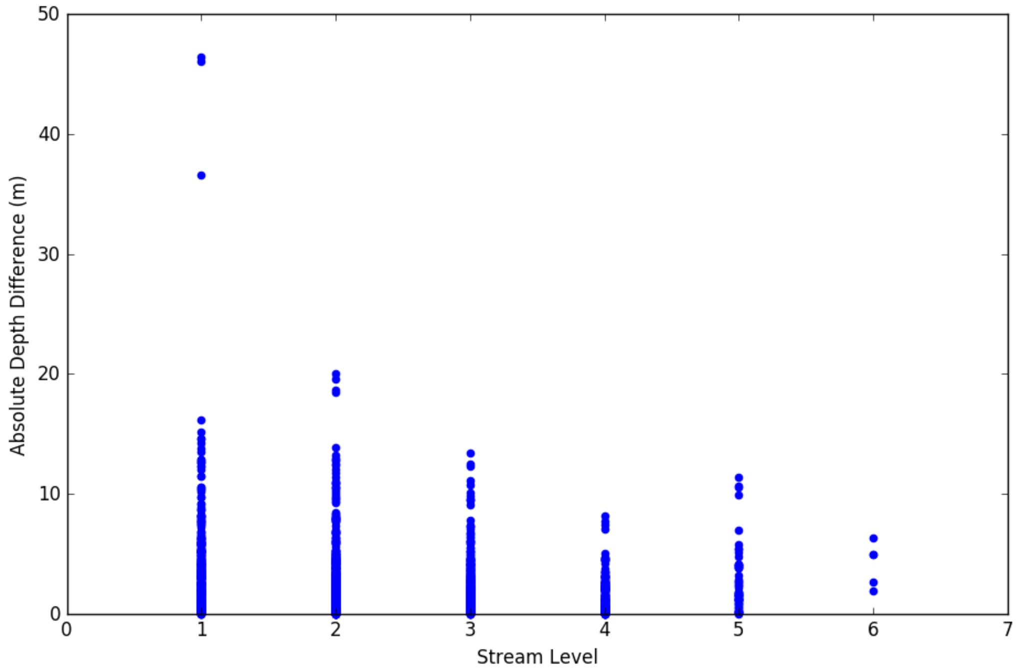

Figure 11. Image shows the correlation between absolute depth differences (error) and stream level for Southeast Texas and the Texas Coast.

As seen in Figure 11, results indicate some relationship/trend between error and stream level, though it is not extremely evident. Smaller stream levels appear to encompass much larger error values (difference in depths) than compared to larger stream levels. Additional analysis was performed at the local scale, which we defined as the extent of a HUC06 basin. Two sample basins results (120200 and 120401, respectively) are depicted.

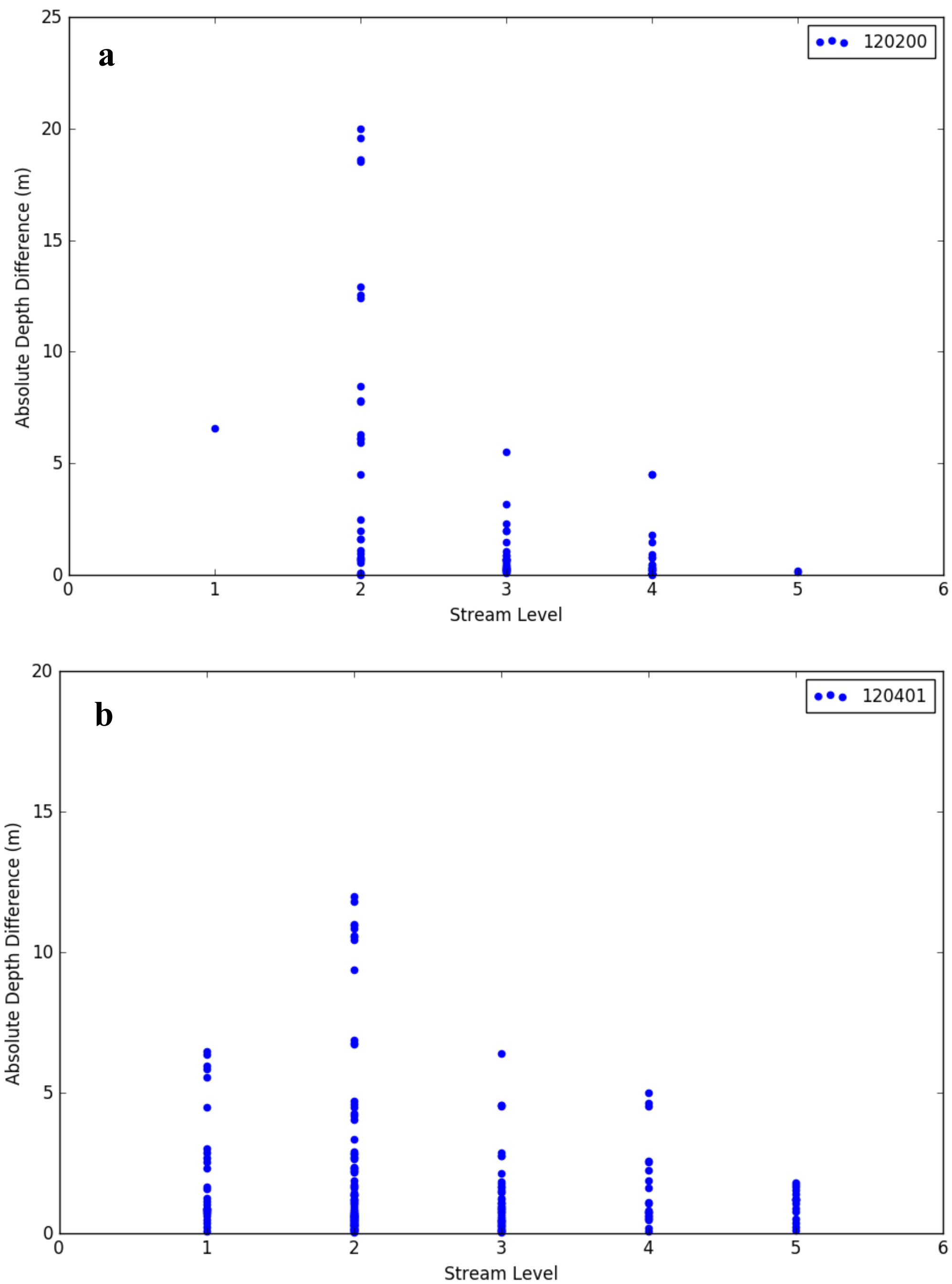

Figure 12. Image *a* shows the correlation between absolute depth differences (error) and stream level for HUC-120200. Image *b* shows the correlation between absolute depth differences (error) and stream level for HUC-120401.

It is evident that analysis by HUC06 basins shrinks the number of data points available for comparisons since this approach essentially bins the data points into different basins, though there remains some indication of a slight trend for both images in Figure 12. Lower stream levels seemingly have higher error values when compared to higher stream levels. This inference is consistent across HUC06 basins. Results from initial investigations depict that there are some trends evident between error and reach length, slope, and stream level. Supplementary analysis is conducted in order to further describe/characterize and illustrate/capture the unique connections between specific terrain characteristics and inaccuracies associated with forecasted inundation maps.

A color-map was generated to represent the spatial distribution of error values (see Figure 13). As seen in the figure, negative error values represent points of under-prediction by the National Water Model when compared to Harvey high water marks and positive error values represent points of NWM over-prediction. We further quantified the distribution of all our data points with a frequency plot (see Figure 14). Our result indicates a nearly normal distribution, although, there is evidence of a slight skew to the right. The data points report a mean and median of -0.26 meters and -0.38 meters, respectively, a standard deviation of nearly 4 meters, and approximately one-third of the predicted inundation depths are within one meter of the measured high water marks. Furthermore, more than one-half (58%) of the error values are reported negative (under-prediction).

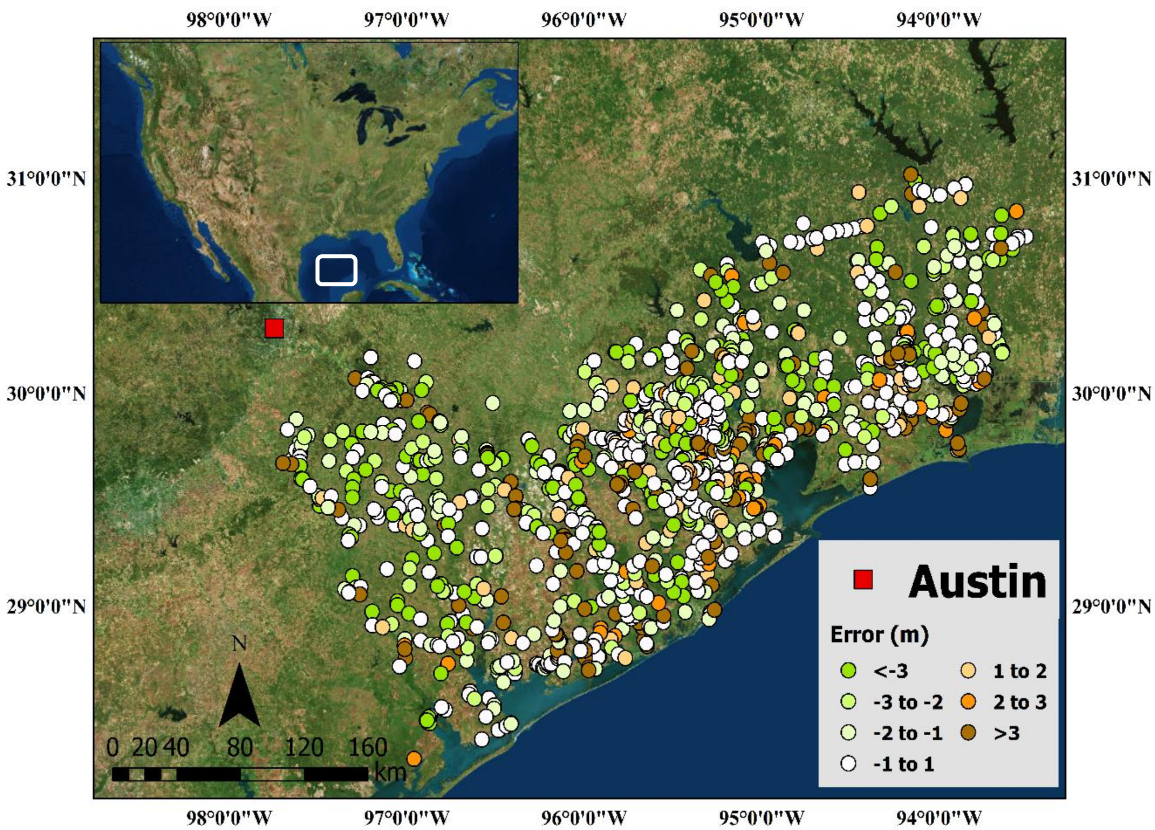

Figure 13. Image depicts the spread of negative (under-prediction) and positive (over-prediction) error values of National Water Model predictions when compared to USGS observed high water marks.

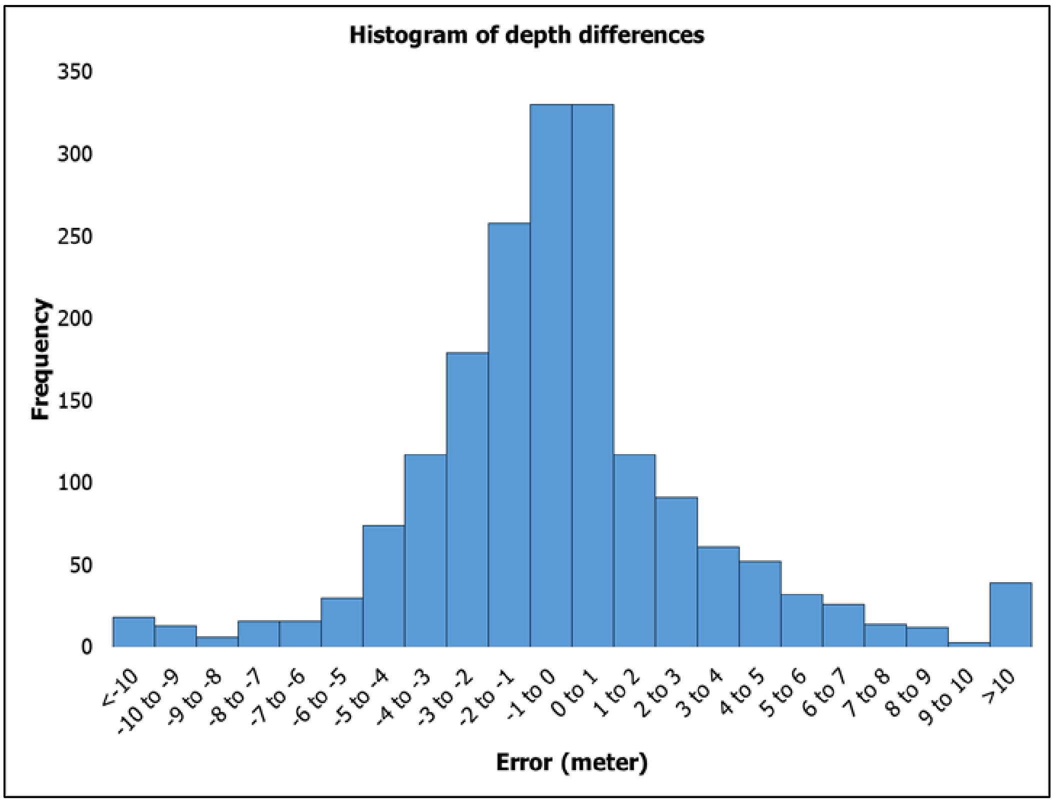

Figure 14. Plot shows the distribution of the measure of National Water Model error.

4.2. Research Question 2: What is the connection between particular terrain characteristics and mapping inaccuracies, and what conclusions can be drawn from assessing the link?

A deeper dive into the data involved the application of additional statistics to further assess and illustrate possible associations between certain channel features and flood prediction accuracies. Results show that differences between peak forecasted depths and measured depths are highest for extreme slope values, though error is much higher for particularly small slopes when compared to error of very large slopes (see Figure 15, image *a*, bin 1: slope < 0.001% and bin 2: 0.10 – 2.3% slope). The presence of a trend is also evident when the variability of error as a function of reach length is quantified by boxplots. Results indicate that there is a slight association between error and reach length though not as profound as the trend evident in the plot of error assessed with channel slope.

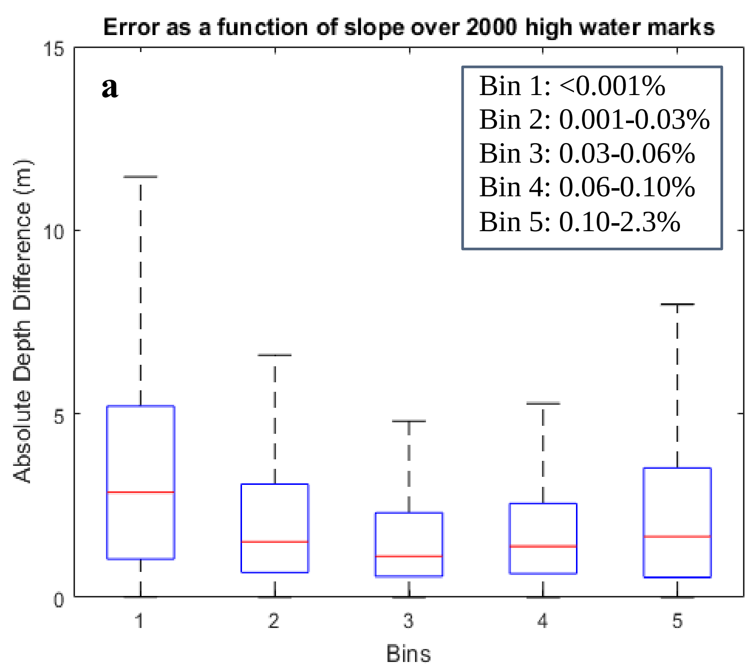

Figure 15: continued next page.

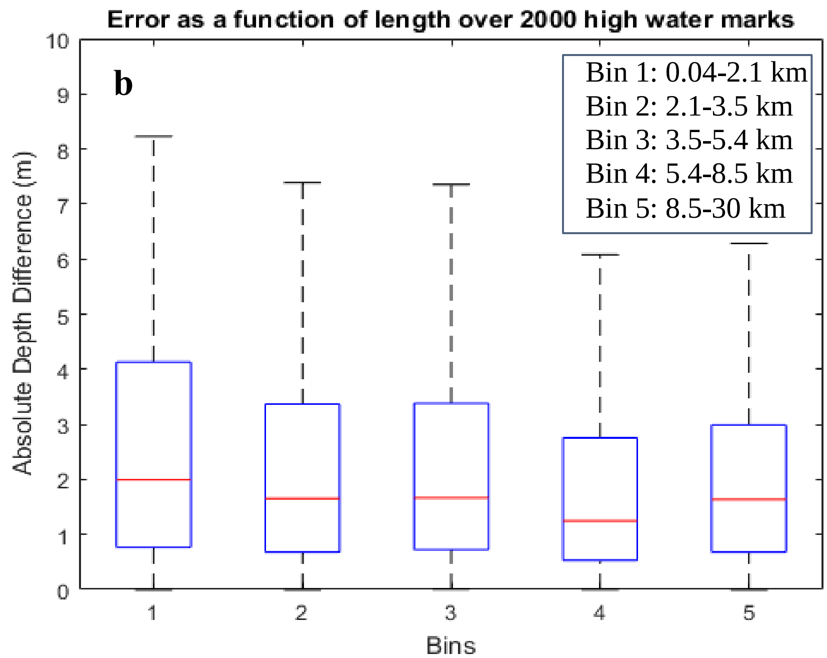

Figure 15. Image *a* shows the correlation between absolute depth differences (error) and slope for all available points of comparison. Image *b* shows the correlation between absolute depth differences (error) and reach length for all points.

This analytical approach is applied to quantify and illustrate the relationship between error and stream level (or classic stream order). As seen in Figure 16, a trend is slightly evident in the boxplot of error by stream level. The largest error values appear to be most dominant for the lowest and highest stream levels. In particular, stream level “6” appears to contain a higher degree of error and variability. A closer analysis of each boxplot reveals that the number of data points allocated to each stream level is unevenly distributed, with stream levels “5” and “6” having 62 and 5 total points, respectively, while stream levels “1” and “2” have 492 and 664 data points, respectively. This means that there is a greater number of channels within our study region that are considered to be main stem channels containing an outlet whereas a considerably smaller percentage of our rivers are represented as tributaries. Based on this finding, stream levels “5” and “6” were combined together in order to more accurately describe the correlation with error for higher stream levels (as seen in Figure 15, image *b*).

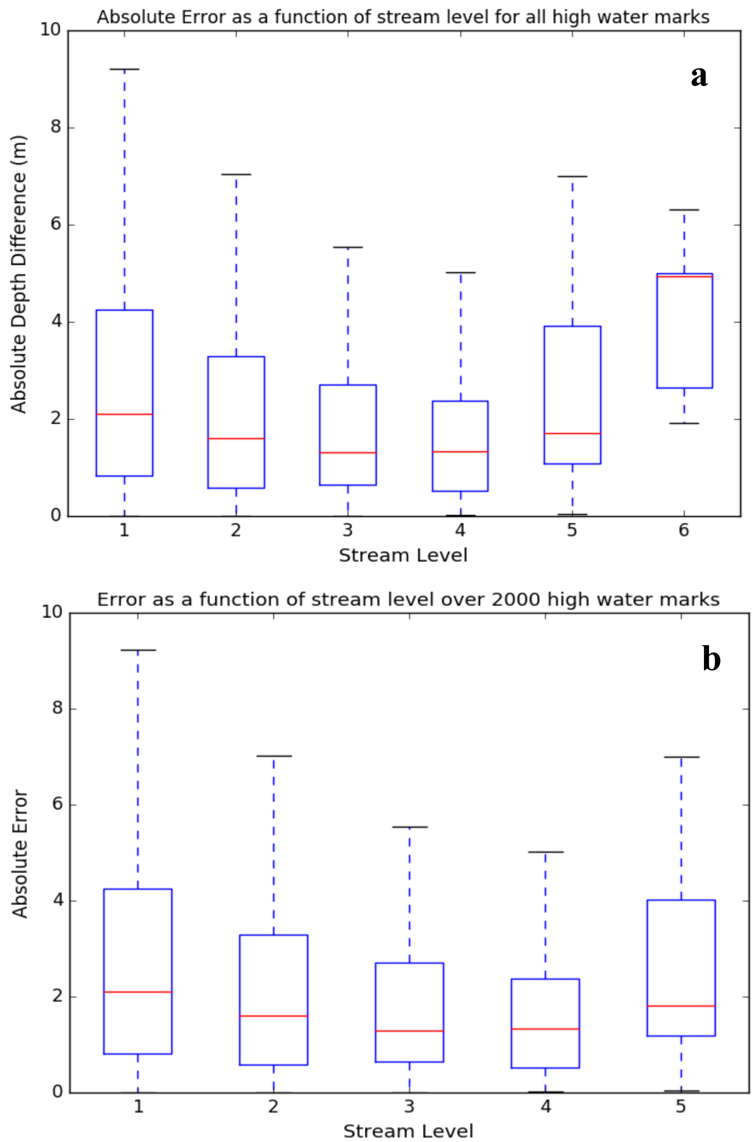

Figure 16. Image *a* shows the correlation between absolute depth differences (error) and stream level for all available points of comparison. Image *b* depicts stream levels "5" and "6" combined.

In order to account for the discrepancy in the number of data points that are available within the lowest and highest stream levels, the error values were normalized by max stage heights corresponding to National Water Model peak forecasted discharges (as seen in Figure 17).

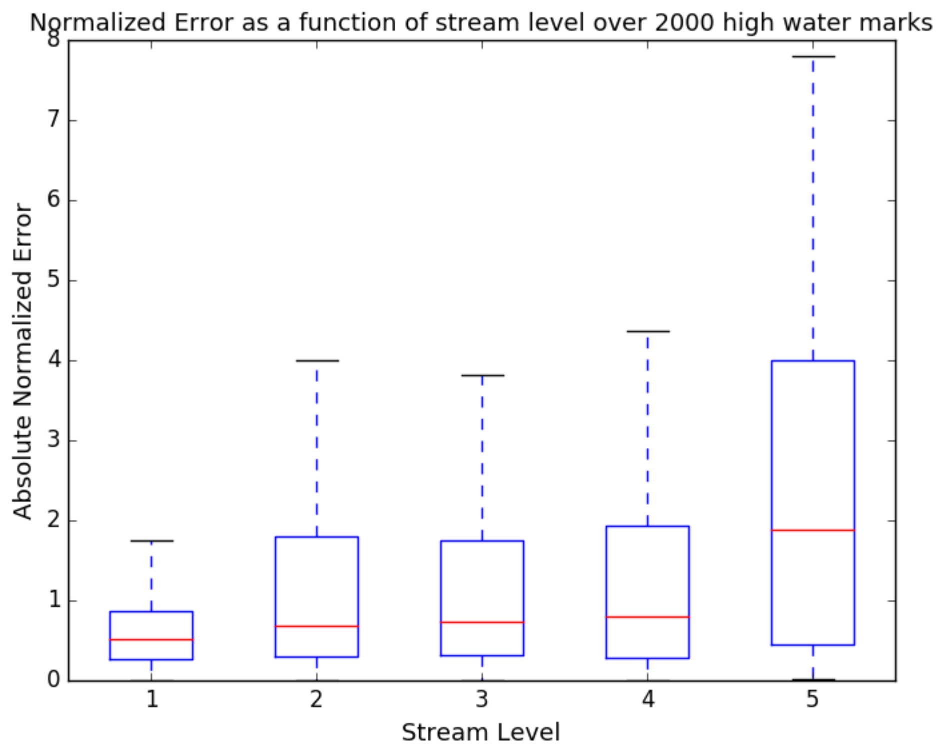

Figure 17. Image depicts normalized error as a function of stream level with stream levels "5" and "6" combined into stream level "5".

Figure 17 depicts the highest stream level (tributaries) as containing the greatest variability in normalized error, and a stream level of "1" contains smaller variability for normalized error.

The next step of analysis involves quantifying the variability of errors for points where the National Water Model has either over-predicted or under-predicted the inundation depth at a reported high water mark. This approach enhances the depth of investigation by localizing, in a sense, possible underlying features that cause overlaps in NWM predictions, specifically.

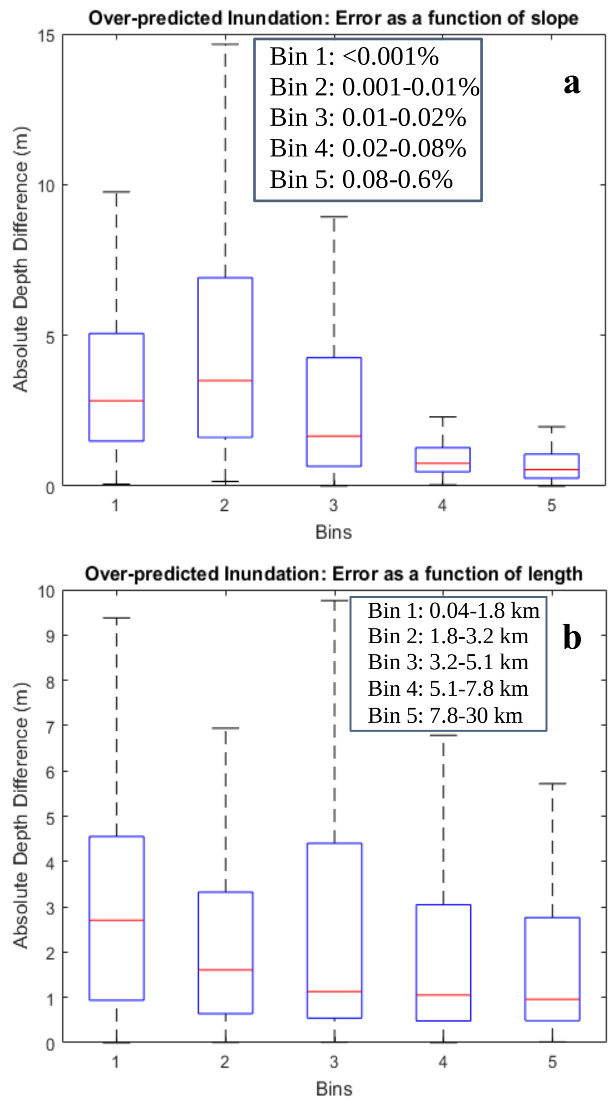

Figure 18. Image *a* shows the correlation between absolute depth differences (error) and slope for NWM over-predicted points. Image *b* depicts error and reach length for over-predicted inundation points.

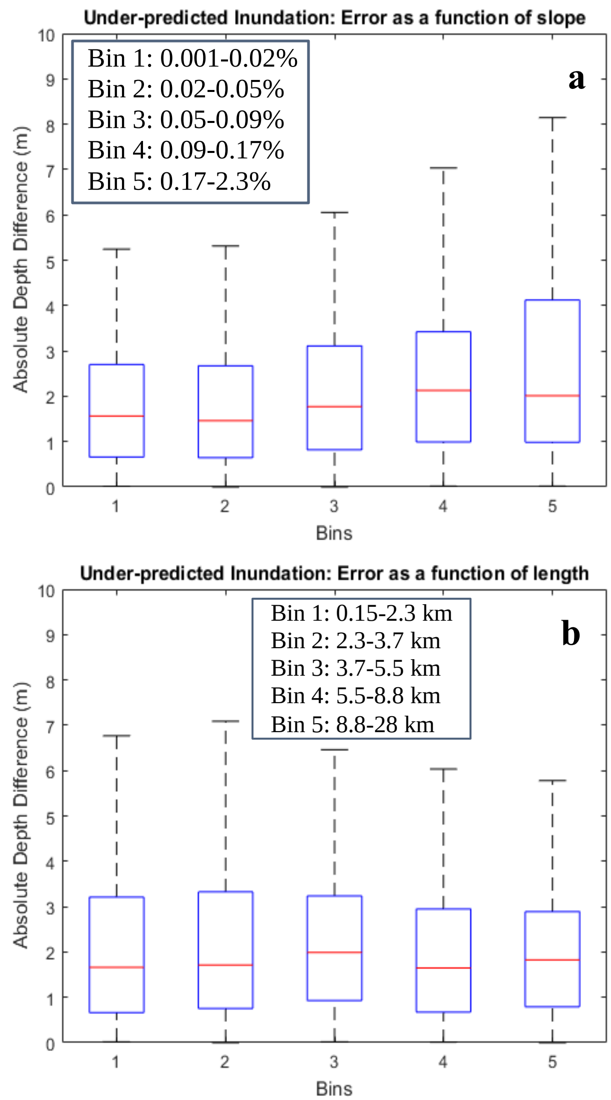

Figure 19. Images *a* and *b* shows the correlation between error by slope and reach length, respectively for NWM under-predicted points.

As seen in Figure 18, a trend is more evident in image *a* (slope) for over-predictions by the National Water Model than image *b* (length), while the presence of a trend is clearly lacking or not as dominant for Figure 19, images *a* and *b* (under-predictions). Error as a function of stream level was also assessed for NWM under- and over-predicted inundations.

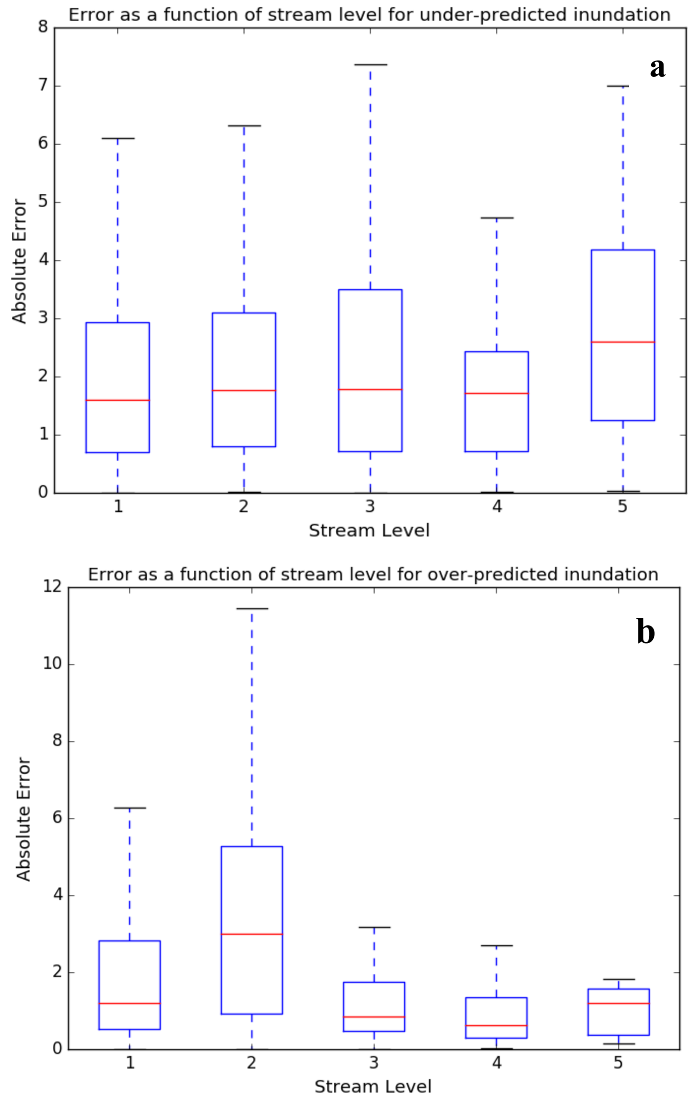

Figure 20. Image *a* shows the correlation between absolute depth differences (error) and stream level for NWM under-predicted points. Image *b* depicts error and stream level for over-predicted inundation points.

Preliminary investigations with boxplots of error by stream level also depict a lack in trend for under-predicted inundation. For over-predictions by the NWM, there is greater variability associated with lower stream levels or channels that are not considered to be tributaries when compared to stream levels of higher order.

4.3. Research Question 3: What steps and/or metrics are feasible for quantifying and minimizing the inconsistencies between predicted and observed values?

There are various solutions with the potential to minimize the differences between predicted and measured data. From a sequential approach, accuracy assessment and minimization can be performed for when 1) rainfall is converted to discharge, 2) discharge is translated to stage height (with a rating curve), and 3) stage height to inundation extent. The last two steps have already been addressed by Godbout *et al*. (in preparation) and Zheng *et al*. (2018). In regards to the first step, converting rainfall to discharge in ways is more relevant towards the entities in charge of gauging stations and various instruments for measuring streamflow data (e.g. AHPS). As such, the topic of the first step is not a focus of this thesis since there are experts who are already leading the charge in assessing instrumentation error and the likes.

Chapter 5: Discussion

The approach taken in this research is, in ways, motivated by previous validation efforts by Zheng *et al*., (2018) in which HAND-derived river geometry (namely channel cross section and length) and synthetic rating curves are verified against calibrated hydrodynamic models (HEC-RAS) under assumed multiple flow conditions. Their work on the validation of synthetic rating curves to HEC-RAS-derived rating curves was not only integral for our approach to quantify the level of disagreement between predicted and observed water depths, but also provided insight on channel features, like Manning's n, that likely influence the discrepancies between model and observations. Work by Godbout *et al*. (in preparation) carried on with the validation of synthetic rating curves to calibrated HEC-RAS models by investigating other channel characteristics such as channel length and slope for three major Texas rivers: 1) San Antonio, 2) Guadalupe, and 3) Colorado (distances are 390 km, 370 km, and 1,387 km, respectively). Descriptive statistics and normalized root mean square error were applied to quantify the variability in stage height for sections of a given channel and to identify possible correlations between model-empirical differences and channel features. Their results indicate that reach length and slope are found to strongly correlate with differences between synthetic rating curves and HEC-RAS-derived rating curves. Furthermore, SRCs are the least accurate for short reaches with extremely low or high slope. See Godbout *et al*. (in preparation), for a complete discussion on synthetic rating curve validations.

5.1. RESEARCH QUESTION 1: WHAT TERRAIN CHARACTERISTICS AND/OR CHANNEL FEATURES AFFECT THE LEVEL OF DISAGREEMENT BETWEEN PREDICTION AND OBSERVED VALUES?

Our analysis of basic channel features (slope and length) endorses the work by Godbout *et al*. (in preparation): slope and length correlate strongly with the level of disagreement, which we defined as error, between predictions (National Water Model forecasted inundation depths) and observations (USGS Harvey high water marks). As seen by our initial studies (see Figures 9 and 10), assessments on a more localized nature are not as significant or telling of trends. For several of the HUC06 basins, the lack of data points makes it challenging to form any single conclusion regarding the pattern of behavior between the parameters. Moreover, for those that appear to contain a satisfactory number of information, there appears to be a lack in trend. The results seen in Figure 9 preclude one from inferring about specific channel characteristics and error. Results of error evaluated with slope for our sample HUC06 basins are slightly more indicative of our previously larger-scaled analysis. As seen in Figure 10, image *b*, a large portion appears to rather exhibit random behavior, causing great difficulty in describing the nature of the relationship between error and slope. Though in comparing across channel features, it is likely that slope may exhibit a stronger weight or dominance than reach length in regards to error correlation.

From our investigation of the spatial distribution of error as well as the frequency distribution of error, we found that in general the resulting NWM prediction has a low bias with a mean difference of 26 cm. However, it is worth noting that there are far larger depth differences at individual locations. Moreover, approximately one-third of the comparisons have less than one meter of vertical difference between the National Water Model forecasted depths and the observed high water marks. Therefore, based on preliminary assessments and previous validation efforts, reach length, slope, and stream level are found at varying degrees to correlate strongly with the levels of disagreement between forecasted observed water levels.

5.2. Research Question 2: What is the connection between particular terrain characteristics and mapping inaccuracies, and what conclusions can be drawn from assessing the link?

From this analysis we find that the presence of pluvial flooding and storm surge is likely to obscure significant trends between these channel factors and prediction accuracy as the National Water Model models only fluvial flooding. We find that in regions where the model over-predicts inundated depth that slope and stream level are strong predictors of accuracy.

From the analysis of all our data points we demonstrated that both slope and stream level appear to be more dominant predictors of error, while reach length typically exhibits a weaker correlation. Investigations into under- and over-prediction values revealed that the presence of a trend is more dominant for locations where the National Water Model has over-predicted the depth of inundation. The presence of a dominant trend for our figures illustrating under-prediction is likely to be obscured by the existence of pluvial flooding, which is not accounted for in the National Water model (as mentioned previously in the thesis). Flooding due to the accumulation of surface water, typically a combination of heavy rainfall and river-based flooding, was predominant for the Texas region impacted by Harvey, and is intrinsic to the observational data collected by the USGS. This is supported by Figure 14 in which a larger percentage of our error values are negative. If pluvial flooding can be represented in the National Water Model, the implication is that the appearance of Figure 14 would likely show National Water Model predictions more approximate to empirical data.

5.3. Research Question 3: What steps and/or metrics are feasible for quantifying and minimizing the inconsistencies between predicted and observed values?

A likely solution to solving step 2 (discharge translated to stage height using a rating curve) is a varying moving-window method to minimize discrepancies between modeled and measured stage heights as suggested in the work by Godbout *et al*. (in preparation). Since short reaches with extreme slope values (particularly small slopes) specifically were found to cause issues in the performance of rating curves (which translate discharge to stage height), the authors proposed an approach to take a weighted average over a moving window length centered on the short reach in order to better represent the slope values. Their results indicate that an optimal moving-window length to recalculate slopes varies for rivers in different terrains (Godbout *et al*., in preparation). This approach can be applied to correct flood mapping accuracies. The hypothesis is that by fixing the issues that are related to the performance of rating curves then mapping inaccuracies can thus be minimized.

In addressing step 3 (conversion from stage height to inundation extent), supplementary analysis can emerge from the application of higher resolution topography (Lidar) to enhance the integrity of flood inundation maps. By introducing higher resolution terrain data, we can extract channel networks that more accurately align with the actual channel information. This enhanced network, in combination with discharge values from the National Water Model, can improve the modeling/mapping of water conditions during an extreme weather event. By addressing the underlying issues in all three fronts, flood mapping and prediction services can be enhanced.

Chapter 6: Future Work and Conclusions

6.1. Future Work

Several opportunities are available for further assessment of National Water Model forecasted inundation maps. Improvements to the model and the produced flood maps can be made in particular with further investigation of reaches with low slope and low stream level. Work by Godbout *et al.* (in preparation) has demonstrated that synthetic rating curves estimated using terrain data in conjunction with the assumption of uniform flow are inaccurate in some cases. Moreover, the optimal length found from the moving window approach may depend on actual terrain characteristics of the river and the surrounding study area. One suggestion that may warrant further studies is to introduce a hydraulic framework (Maidment *et al.*, 2017) that aims to improve the HAND mapping method, and which results in a uniformly distributed channel length. The incremental length is informed by investigations into the optimal moving window length for a specified channel network. The idea is then to modify the heterogeneity seen in the NHDPlus networks into more uniformly distributed reach lengths in order to re-calculate their slope values. An improved channel slope can enhance the integrity of the synthetic rating curves and thus increase flood mapping accuracy.

Another promising suggestion is to develop HAND into a completely new model which incorporates hydraulic information as well as a physical component. The convenience of the current HAND method is in its ability to create flood inundation maps for the contiguous U.S. without requiring detailed measurements. A new capability that the HAND method can offer, and still retain the flood mapping component, is stored local hydrodynamic information that is continually updated and informed by stream gages. This information would be made available and accessible in the cloud (cloud-based real time information). Furthermore, an improved HAND method can include an automatic detection ability that identifies true channel bottoms and standardizes to a geodetic datum based on the input terrain dataset. With the detection scheme, it would be instructive to quantify the uncertainty that originates from the terrain dataset as well as its impact on forecasted inundation depth.

In relation to the terrain, additional investigations can include more local elements such as flatness and urban versus rural areas in addition to lidar (Ozdemir *et al*., 2013). Subsequent questions to consider are which metrics are effective in quantifying their impact at the scale of flood inundation maps, and is there a degree of interaction between them such that they may further erode the integrity of flood inundation maps. Error metrics, geostatistics, and likely flood inundation maps based on probabilistic rating curves (Ocio *et al*., 2017) all can be instructive in identifying the potential characteristics that are associated with our factors of interest. In particular, geostatistics can be applied to assess correlations between model errors in order to determine whether error trends are more spatially distributed. Furthermore, since the National Water Model solely accounts for fluvial flooding, the expectation is that correlations between model errors are more relatively similar to each other along the coast than further inland because additional drivers such as storm surge are not modeled. The results from this project are overall encouraging considering that the National Water Model predictions are based on purely remote sensed terrain data with a 10-meter resolution. Between the increasing availability of Lidar and the analysis of channel features affecting accuracy, it is evident that there is an immense capacity for improvement. Additional methods to evaluate forecasted inundation maps may demand higher resolution topography data (lidar) in conjunction with GeoNet to automatically identify flow paths that accurately align with the channelized terrain (Passalacqua *et al*., 2010a; 2010b; 2012; Sangireddy *et al*., 2016.).

6.2. Concluding Remarks

The results of comparisons between the National Water Model inundation extent and the database of high water marks show that the predicted extent has low bias over a large spatial extent. Analysis of the results demonstrate that the inaccuracies of National Water Model forecasted inundation maps are largely correlated with extreme slope values and stream level. Improvements to the model and the produced flood maps can be made in particular with further investigation of reaches with low slope and low stream level. Furthermore, channel length does not appear to be a strong predictor of error. Lastly, the need for real-time inundation maps cannot be overstated. Current and future findings can help illuminate possible measures to improve the quality of flood inundation mapping, and hopefully our understanding of hurricane hydrology. From an operational standpoint, this improved understanding can allow us to make that jump or connection to providing actionable intelligence for first responders, and an overall improved capability to respond to extreme weather events.

Appendix

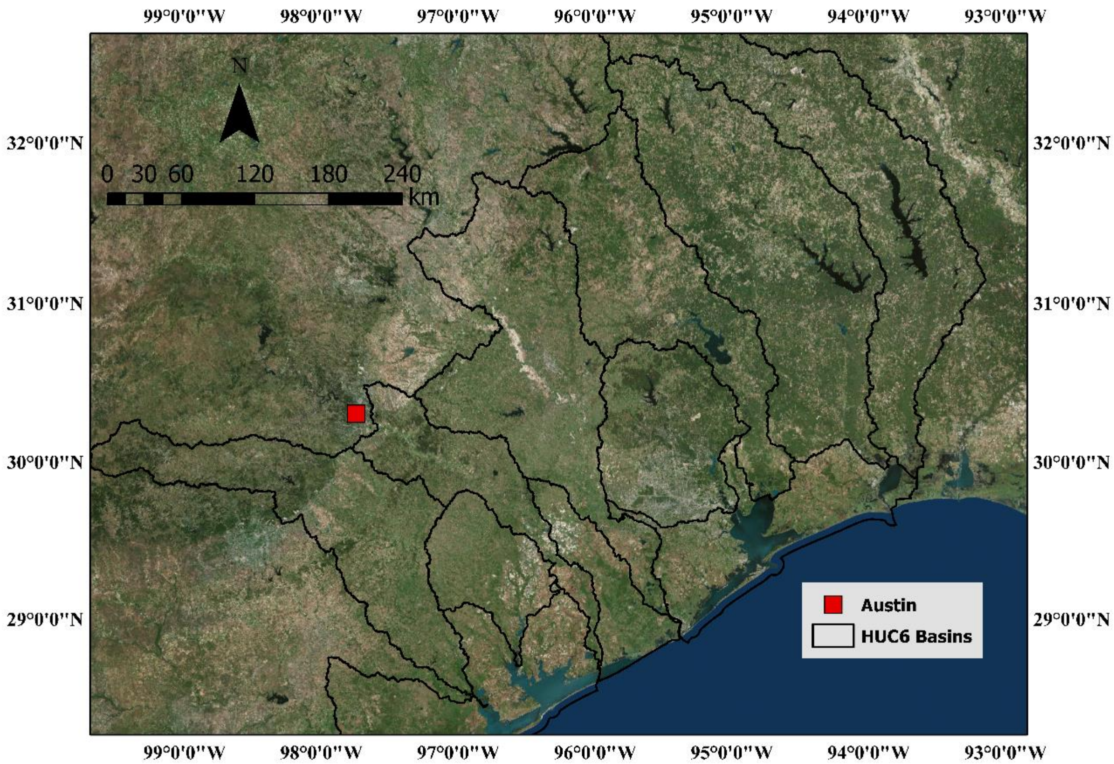

Figure A1. Hydrologic Unit Code (HUC) 6 basins within the study region.

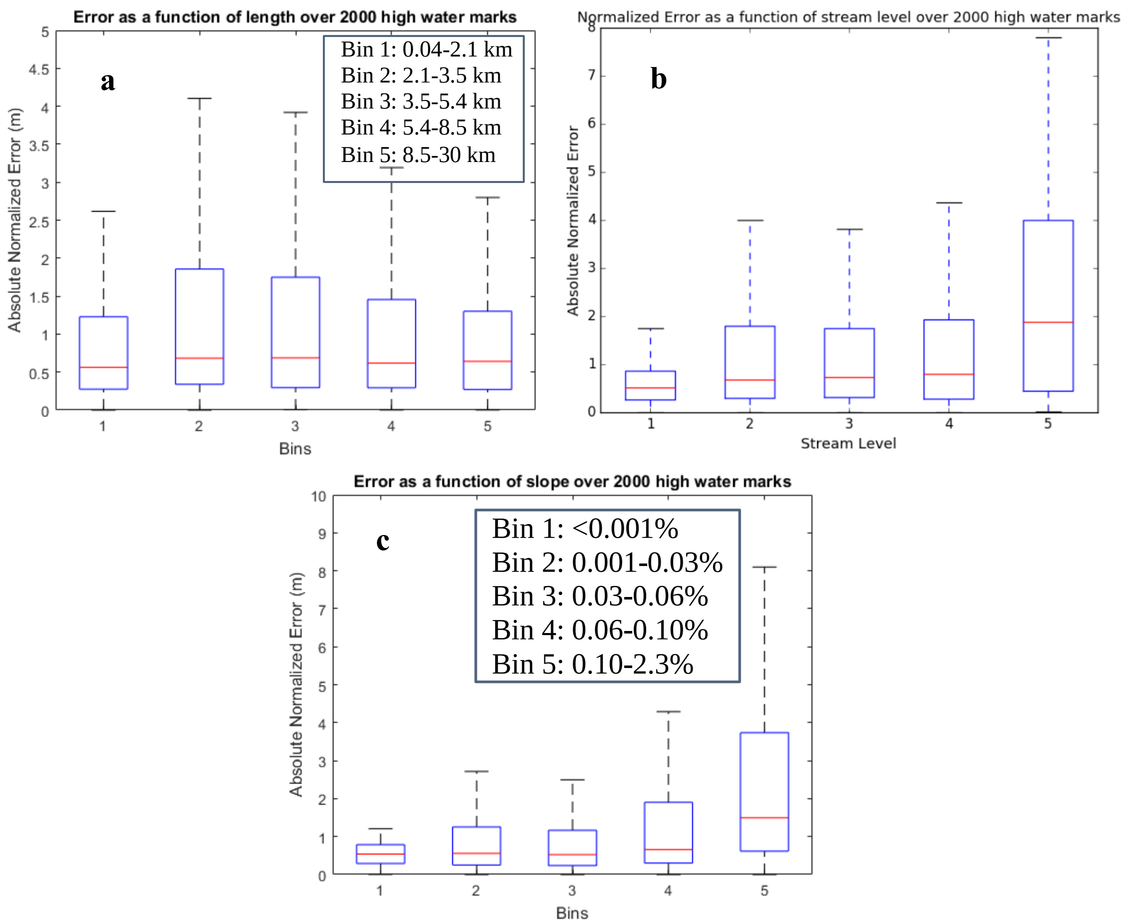

Figure A2. Image *a* shows normalized absolute error as a function of length for all high water marks. Image *b* shows normalized absolute error as a function of stream level. Image *c* shows normalized absolute error as a function of slope.

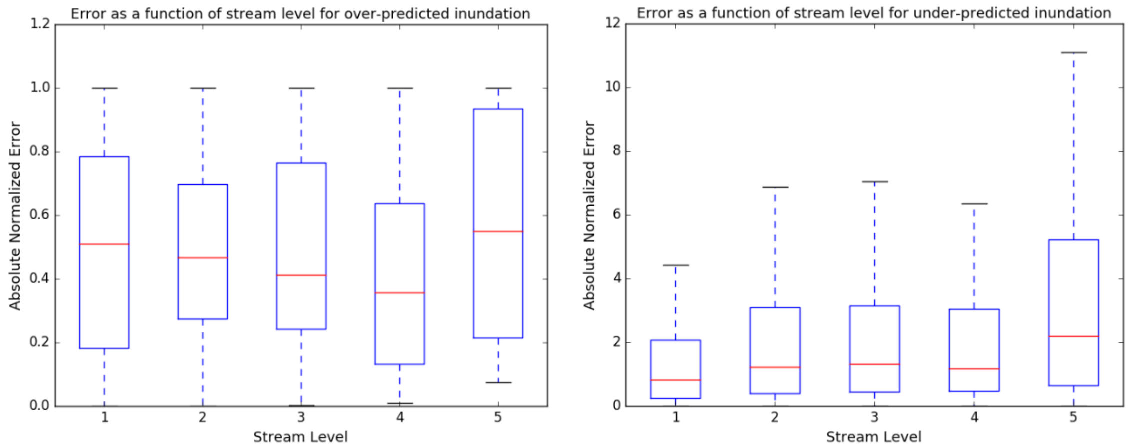

Figure A3. Image *a* shows normalized absolute error as a function of stream level for over-predicted inundation by NWM. Image *b* shows normalized absolute error as a function of stream level for under-predicted inundation.

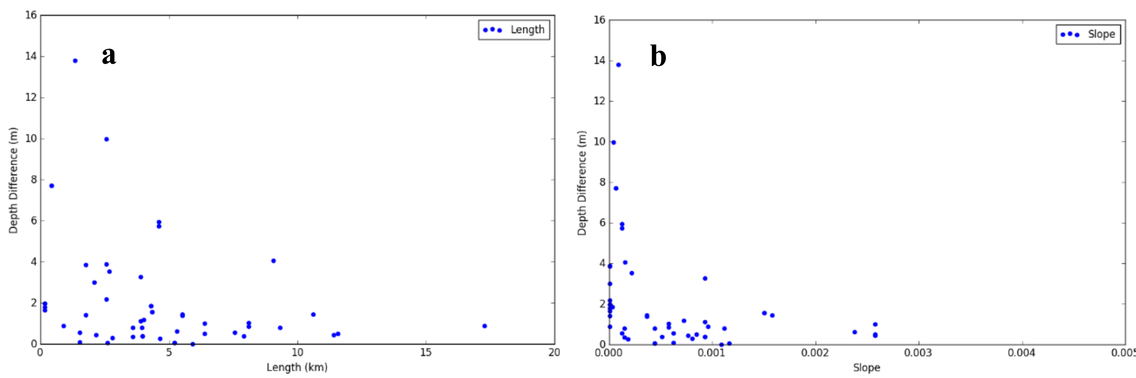

Figure A4. Image *a* shows error as a function of length for HUC6 – 120100. Image *b* shows error as a function of slope for 120100.

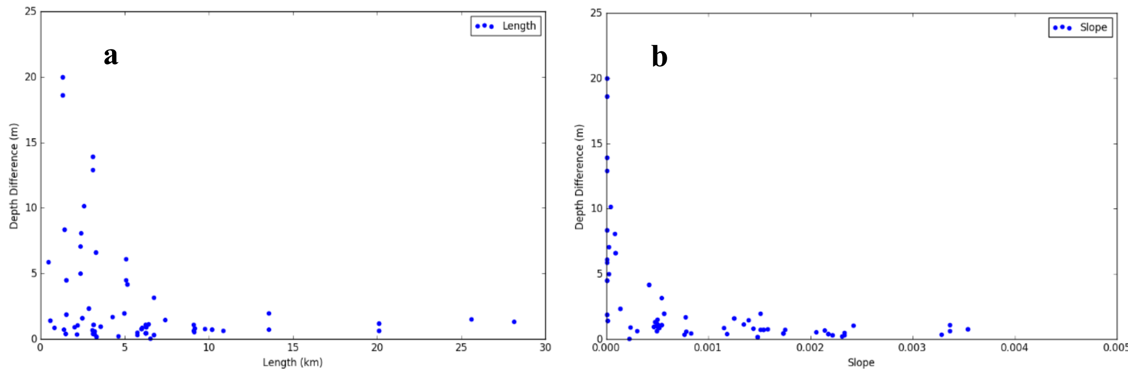

Figure A5. Image *a* shows error as a function of length for HUC6 – 120200. Image *b* shows error as a function of slope for 120200.

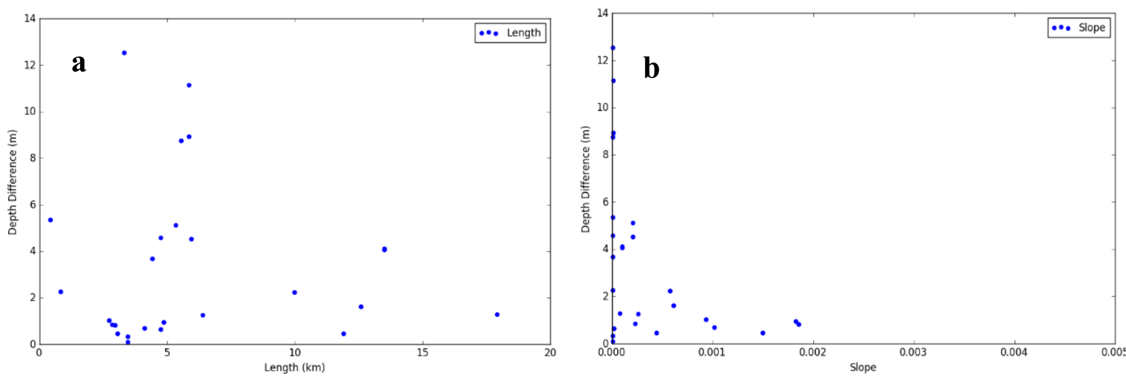

Figure A6. Image *a* shows error as a function of length for HUC6 – 120302. Image *b* shows error as a function of slope for 120302.

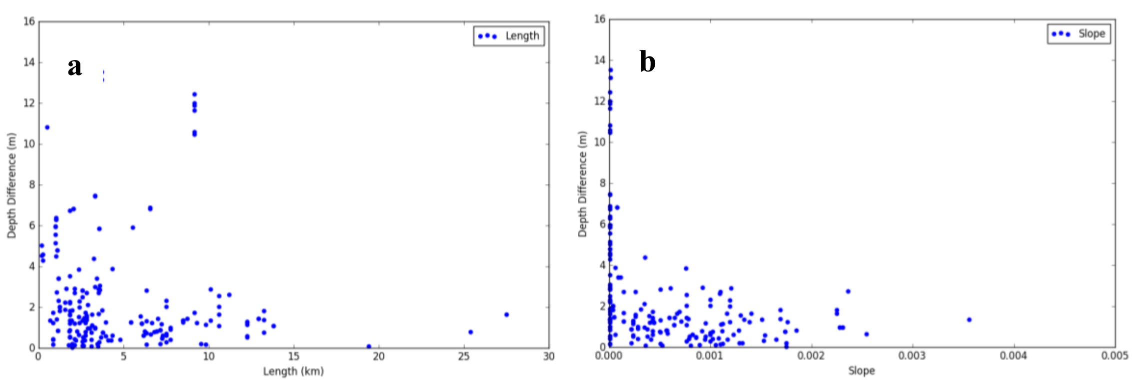

Figure A7. Image *a* shows error as a function of length for HUC6 – 120401. Image *b* shows error as a function of slope for 120401.

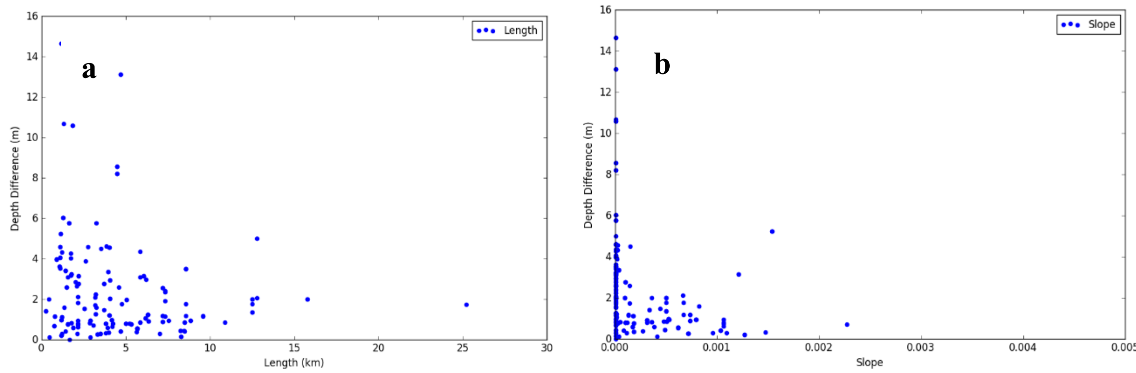

Figure A8. Image *a* shows error as a function of length for HUC6 – 120402. Image *b* shows error as a function of slope for 120402.

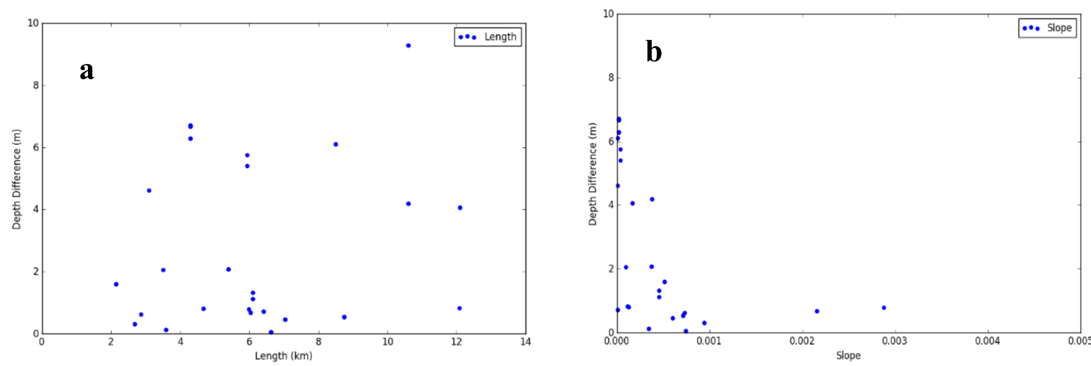

Figure A9. Image *a* shows error as a function of length for HUC6 – 120701. Image *b* shows error as a function of slope for 120701.

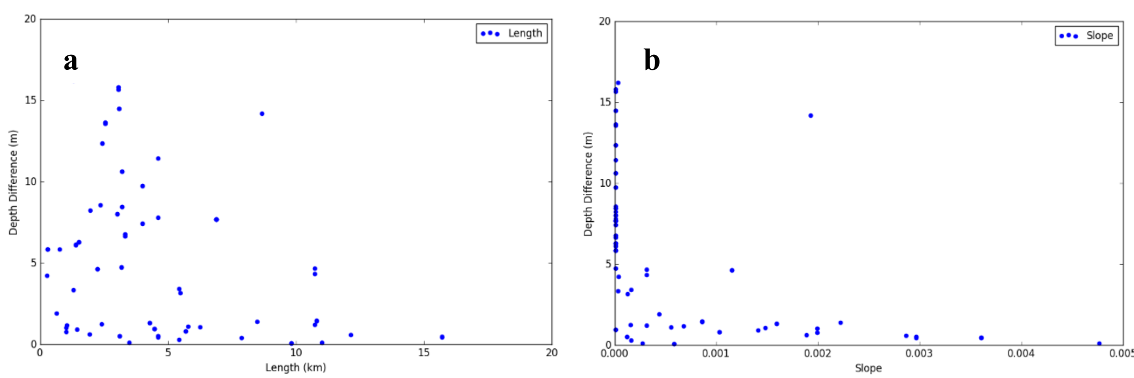

Figure A10. Image *a* shows error as a function of length for HUC6 – 120903. Image *b* shows error as a function of slope for 120903.

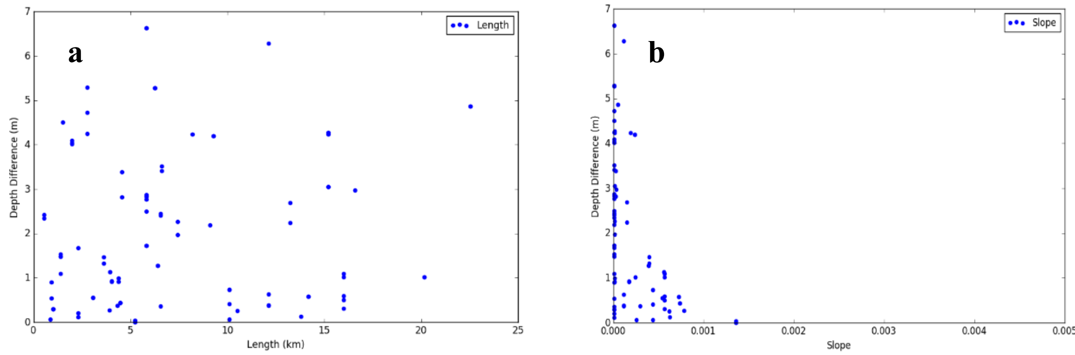

Figure A11. Image *a* shows error as a function of length for HUC6 – 120904. Image *b* shows error as a function of slope for 120904.

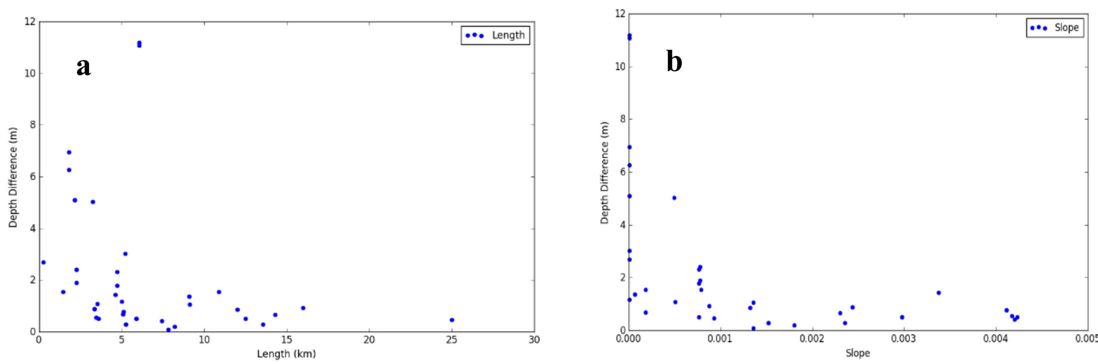

Figure A12. Image *a* shows error as a function of length for HUC6 – 121001. Image *b* shows error as a function of slope for 121001.

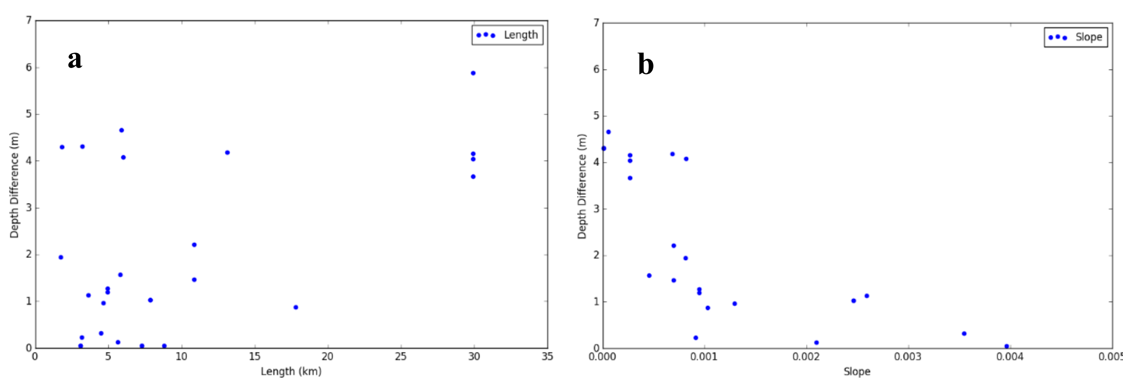

Figure A13. Image *a* shows error as a function of length for HUC6 – 121002. Image *b* shows error as a function of slope for 121002.

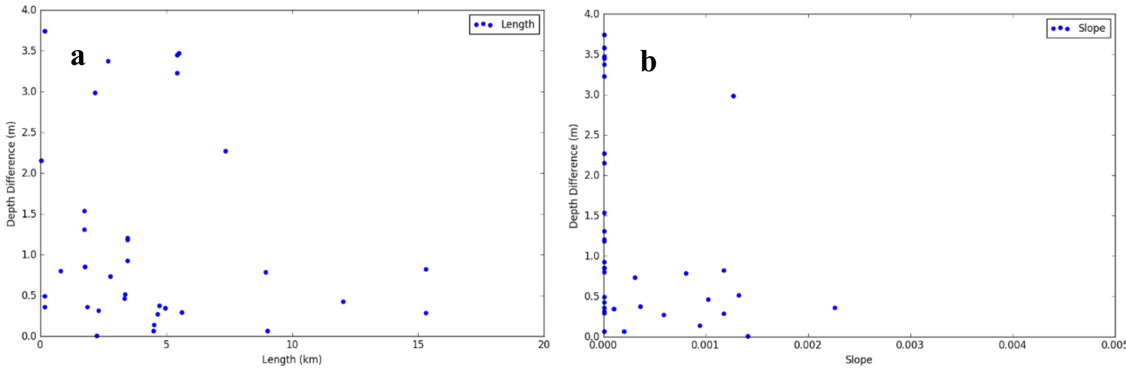

Figure A14. Image *a* shows error as a function of length for HUC6 – 121004. Image *b* shows error as a function of slope for 121004.

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